Scientific opportunities for developing essential biodiversity variables from satellite remote sensing in the context of the post-2020 global biodiversity framework

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Abstract

Satellite remote sensing (SRS) provides huge potential for tracking progress towards achieving global conservation targets and goals. To make a transformative impact, SRS workflows should be tailored towards the requirements of ecological users and policymakers. Here, we assess requirements from the post-2020 global biodiversity framework of the Convention of Biological Diversity (CBD) by ranking the use of SRS products in biodiversity indicator workflows. Fifty unique indicators were identified for tracking the state of terrestrial biodiversity, spanning two goals and six targets across seventeen target components. Twentynine indicators shared enough information to analyse workflows and to classify underlying (spatial information) products into the Essential Biodiversity Variable (EBV) framework. We further quantified the policy relevance of EBVs by counting EBV usage across the CBD goals and targets. Combined with scores on the technical feasibility, accuracy, and immaturity of SRS products, we then identified which EBVs offer promising opportunities for workflow development from SRS. Top priority SRS products included the fraction of vegetation cover, plant area index profile, above-ground biomass, foliar N/P/K content, land cover (vegetation type), leaf area index, carbon cycle (above-ground biomass), chlorophyll content & flux, ecosystem fragmentation, ecosystem structural variance, and gross primary productivity. Our results showed that spatial information products related to ecosystem distribution, live cover fraction and species distribution EBVs are currently most widely used in the CBD context, while primary production and physiology EBVs remain under-used. To advance the monitoring of ecosystem distributions, harmonized and high resolution SRS products with higher thematic detail on specific ecosystems and habitat types are needed. Likewise, live cover fraction EBVs (e.g. fraction of vegetation cover and plant area index profile) would require developing and harmonizing ecosystem taxonomies and relating the fraction of vegetation (functional) types to a desired ecosystem reference state. Finally, to enable the monitoring of plant species phenology, stoichiometry and alien invasive species (impact), novel workflows need to combine very high resolution and multi-spectral satellite observations for mapping and monitoring the physiological traits of plant species (e.g. leaf area index, chlorophyll content & flux, and foliar N/P/K content). Capitalizing on these opportunities for SRS-enabled EBVs could improve the tracking of CBD goals and targets, e.g. in the context of ecosystem restoration, productivity and sustainability of agricultural and forested ecosystems, effective management of protected areas, reduction of species extinction rates, or a better management of the impact of alien invasive species.

Keywords:
Action targets, earth observation, ecological governance, global observing system, prioritization, systematic review

1 Introduction

Global biodiversity is rapidly declining and human impacts impair the distribution and abundance of wild species, the distinctness of ecological communities, and the extent and integrity of ecosystems. Since the 1992 Rio Earth Summit, the Convention on Biological Diversity (CBD) has aimed to promote sustainable development and conservation of biodiversity through national policies. In 2010, after realizing that a significant reduction of the rate of biodiversity loss had not yet been achieved, the CBD agreed to a strategic plan with twenty Aichi biodiversity targets for the period 2011—2020. These 20 targets aimed at addressing the underlying causes of biodiversity loss, reducing direct pressures on biodiversity, and improving the status of biodiversity. Although none of these 20 targets have been met in full (Butchart et al., 2016), they have played a critical role in defining the global agenda for conservation and in influencing policy and action. Governments are now developing the post-2020 global biodiversity framework which will guide actions for decades to come, which includes monitoring progress towards a new set of ambitious goals and targets (CBD, 2021).

Assessments of progress towards national and global conservation goals and targets requires a multitude of datasets that can feed into biodiversity indicators. The development of such datasets could benefit from a globally coordinated observing system that provides a minimal set of fundamental biodiversity observations in a standardized and harmonized way (Navarro et al., 2017). In this context, Essential Biodiversity Variables (EBVs) have been introduced by the Group on Earth Observations Biodiversity Observation Network (GEO BON) as a standard framework for biodiversity monitoring (Pereira et al., 2013). Specifically, the EBV framework allows to prioritize a minimum set of measurements needed for studying, reporting and managing major dimensions of biodiversity change (Pereira et al., 2013). Similar to Essential Climate Variables (ECVs), which were introduced by the Global Climate Observing System (GCOS) (Bojinski et al., 2014), EBVs provide an intermediary abstraction layer between primary (raw) observations and high-level biodiversity indicators used for policy. EBVs thus facilitate the integration and harmonization of heterogeneous raw data and provide a framework for national monitoring programs (Navarro et al., 2017). EBVs have to be sensitive to changes at policy relevant time scales (i.e. decades rather than centuries) and applicable across spatial scales (from local to global) to allow tracking of progress towards biodiversity targets in a cost-effective manner (Pereira et al., 2013). While GEO BON currently distinguishes six EBV classes and twenty EBVs (https://geobon.org/ebvs/what-are-ebvs/), development of EBV data products and associated workflows by the scientific community is ongoing and often challenged by the spatial, temporal and taxonomic gaps of existing monitoring schemes (Proença et al., 2017).

Besides *in-situ* monitoring, satellite remote sensing (SRS) plays a vital role in the development of EBVs and reliable indicators, especially in the terrestrial realm (Pettorelli et al., 2016; Skidmore et al., 2015). Currently, SRS provides the only method for acquiring spatially contiguous data on biodiversity and ecosystems with a (near-) global extent and long-term coverage. While SRS products have often been envisaged in the context of extrapolating point observations of species distribution and abundance from *in-situ* monitoring into continuous variables in space and time (Pereira et al., 2017), recent studies also emphasize a subset of SRS products for the direct monitoring of terrestrial EBVs from space (Alleaume et al., 2018; Pettorelli et al., 2016; Skidmore et al., 2021, 2015). For instance, SRS products of fractional cover, forest cover or land cover can capture EBVs related to ecosystem distribution, fragmentation, and heterogeneity (Skidmore et al., 2015), and forthcoming satellite sensor missions could even enhance the ability to retrieve species-specific plant traits (Kissling et al., 2018). With an increasing amount of SRS products becoming available (Kuenzer et al., 2014) and new satellite missions and sensors emerging, the range of observations that can directly contribute to the development of EBVs will broaden. Examples include hyperspectral radiometers for estimating phylogenetic and trait diversity of plants (Asner et al., 2017), or radar and LiDAR sensors for measuring 3-D ecosystem structure from space (Valbuena et al., 2020). However, an overview of how SRS products are connected to EBVs in the context of the post-2020 global biodiversity framework is currently lacking.

Identifying priorities and scientific opportunities for developing SRS-enabled EBV workflows in the global policy context requires to link the long-term goals and medium-term targets with product requirements (Paganini et al., 2016). Space agencies often develop these requirements by assessing the feasibility, accuracy and (im)maturity of SRS products (Skidmore et al., 2021), e.g. regarding technical specifications of current-day sensors (Kuenzer et al., 2014), the potential of novel approaches (Skidmore et al., 2021, 2015), the operational

capability of processing chains (Paganini et al., 2016), or the validity of data products (Mayr et al., 2019). Such assessments provide a high level of technological detail useful for space agency engineers and SRS scientists, but are difficult to understand by ecologists and policy makers (Kuenzer et al., 2014; O'Connor et al., 2015). On the other hand, reviews of EBVs and conservation policies often come with little detail on specific requirements that would be needed by SRS developers. To our knowledge, only a few reviews (O'Connor et al., 2015; Schmeller et al., 2018; Vihervaara et al., 2017) have bridged the gap between policy, remote sensing and biodiversity experts by propagating individual conservation targets to SRS requirements. However, the relevance of their findings for the post-2020 framework is limited considering their focus on national conservation targets (Vihervaara et al., 2017) or on the previous set of Aichi targets (O'Connor et al., 2015). No detailed user requirement analysis of SRS products has yet been performed in the specific context of the post-2020 global biodiversity framework of the CBD, severely limiting the capacity of the SRS community to contribute to the development of SRS-enabled EBV workflows and uptake of these EBVs in biodiversity indicators.

Here, we assess the post-2020 global biodiversity framework with the aim to identify scientific opportunities for developing new SRS-enabled EBV workflows for tracking the state of terrestrial biodiversity. We first review the goals, targets, and target components of the post-2020 global biodiversity framework and filter for those containing elements that monitor the state of terrestrial biodiversity with SRS (Figure 1, top). We then analyse workflows of associated biodiversity indicators and summarize which spatial information products are used. By classifying each product into the EBV framework (Figure 1, bottom) and counting the usage of different EBVs, we assess the relevance of such products in the CBD policy context. Together with scorings of the feasibility, accuracy and (im)maturity of SRS products from a recent expert assessment (Skidmore et al. 2021), we create a prioritization and ranking of SRS products and associated EBVs. A final analysis identifies the consequences of this prioritization on the CBD long-term goals and medium-term targets if the scientific development focuses only on the workflows for the priority list (Figure 1, left). With this approach, our user-requirement analysis integrates policy, SRS and ecology and thereby provides a new view on which SRS workflows could be developed for an improved tracking of global biodiversity change.

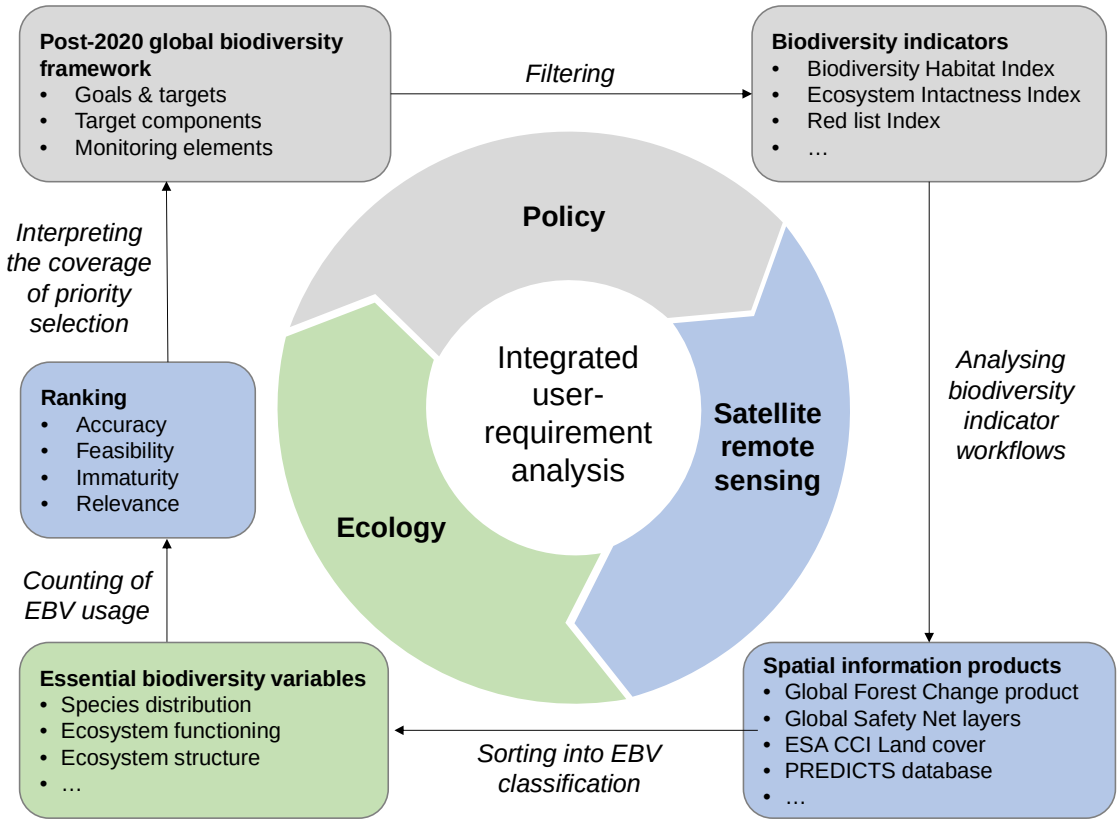

Fig. 1. Conceptual approach of the integrated user requirement analysis which takes policy, satellite remote sensing and ecology into account. The assessment of the goals, targets, target components and monitoring elements of the post-2020 global biodiversity framework allows to identify policy-relevant biodiversity indicators that track the state of terrestrial biodiversity with spatial information products. Products used in indicator workflows can be classified into the essential biodiversity variable (EBV) framework, and the usage of EBVs provides their relevance for the policy goals and targets. Together with scores of the technical feasibility, accuracy and (im)maturity of satellite remote sensing products, a prioritization and ranking can be performed which identifies the opportunities for developing EBV workflows from satellite remote sensing.

2 Methodology

Our methodology for analysing scientific opportunities for developing SRS-enabled EBVs included a top-down review and a bottom-up expert assessment (Figure 2). The top-down review (Figure 2, left) allowed us to quantify the relevance of specific EBVs for future (geospatial) monitoring of global and national (terrestrial) biodiversity goals and targets, whereas the bottom-up expert assessment (Figure 2, right) provided information on the technical feasibility, accuracy, and maturity of biodiversity-relevant satellite products (Skidmore et al. 2021). Together, the scores from the four criteria (relevance, feasibility, accuracy and (im)maturity) were used for ranking SRS products and for analysing the consequences of focusing solely on a priority selection (Figure 2). This allowed us to identify scientific opportunities for developing SRS-enabled EBV workflows.

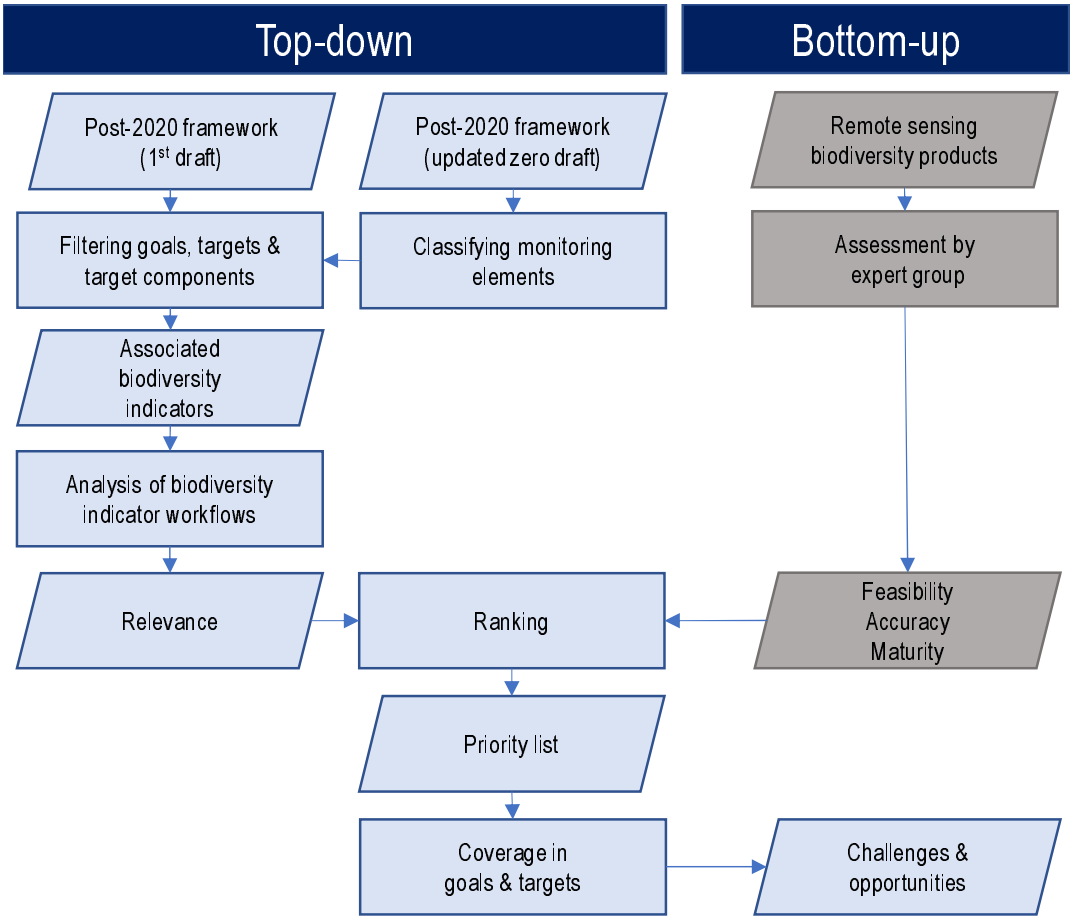

Fig. 2. Methodology for ranking and impact analysis, combining a top-down review (left) with an expert assessment (right). Left: The goals, targets, target components and monitoring elements listed in the post-2020 global biodiversity framework are filtered to track the state of terrestrial environments using for remotely observable characteristics. Workflows of associated biodiversity indicators are analysed for the relevance of satellite remote sensing (SRS) products and related essential biodiversity variables (EBVs). The relevance score is one of the four ranking criteria. Right: Remote sensing biodiversity products assessed by an expert group in terms of the other three criteria feasibility, accuracy and (im)maturity (Skidmore et al., 2021). The combined scores of these criteria enabled us to create a priority list for developing EBV workflows from SRS. This allowed us to identify challenges and opportunities for developing EBV workflows from SRS by analysing the coverage and usage of EBVs in the indicators associated with the CBD goals and targets. Colours of different components indicate which activities were performed within this research (blue) and which are extracted from a recent bottom-up expert review (Skidmore et al., 2021) (grey).

We started the top-down review in 2020 with the updated zero draft of the post-2020 global biodiversity framework (CBD Secretariat, 2020), and then updated this review with the first detailed draft released in June 2021 (CBD, 2021). The framework defines four goals for 2050 (A–D), and 21 targets for 2030 with 72 target components (CBD, 2021). Here, goal A and the targets 1–7 focus on 'reducing threats to biodiversity', goal B and targets 8–12 on 'meeting people's needs through sustainable use and benefit-sharing', goals C and target 13 on 'genetic resources', and goal D and targets 14–21 on 'tools and solutions for implementation and mainstreaming'.

Table 1 Glossary of key terms. The list captures key terms, descriptions, and an example focused around target 2 in goal A of the post-2020 global biodiversity framework.

Key term	Description	Example
Goal	Four long-term goals (A, B, C, D) are defined by the post-2020 global biodiversity framework of the CBD to be achieved by 2050.	Goal A: The integrity of all ecosystems is enhanced, with an increase of at least 15 per cent in the area, connectivity and integrity of natural ecosystems, supporting healthy and resilient populations of all species, the rate of extinctions has been reduced at least tenfold, and the risk of species extinctions across all taxonomic and functional groups, is halved, and genetic diversity of wild and domesticated species is safeguarded, with at least 90 per cent of genetic diversity within all species maintained.
Target	For each goal, several action-oriented conservation targets are defined (21 in total) to be met in 2030.	Target 2: Ensure that at least 20 per cent of degraded freshwater, marine and terrestrial ecosystems are under restoration, ensuring connectivity among them and focusing on priority ecosystems.
Target component	Each target is divided into target components to aid in the tracking of progress towards that target.	Target 2 is divided into two target components, including T2.2 'Connectivity'.
Monitoring element	In the updated zero draft of the post-2020 global biodiversity framework (only), each target component was broken up into elements to aid the selection of biodiversity indicators.	For the 'Connectivity' target component six monitoring elements are defined, including the 'Trends in extent and rate of change of terrestrial ecosystems'
Biodiversity indicator	To track the progress of each goal and target a set of (headline, component and complementary) biodiversity indicators (promoted by the Biodiversity Indicators Partnership) are defined.	For goal A, 15 biodiversity indicators have been identified to track the status of terrestrial biodiversity, including the 'Biodiversity Habitat Index' (Hoskins et al., 2016) and the 'Species Protection Index' (GEOBON, 2015).
Biodiversity indicator workflow	The analytical steps needed to process data (from remote sensing or in-situ observations) into biodiversity indicators.	The 'Biodiversity Habitat Index' is calculated by the Biogeographic modelling Infrastructure for Large-scale Biodiversity Indicators (Hoskins et al., 2020) to map of spatial patterns of the distribution of biodiversity.
Satellite remote sensing product	Satellite remote sensing (SRS) product are derived from satellite imagery, here referring to those which capture aspects of biodiversity and ecosystems (Skidmore et al., 2021).	The Global Forest Cover product (Hansen et al., 2013) is used (with additional biodiversity data) to calculate the 'Biodiversity Habitat Index'.
Essential biodiversity variable	Essential biodiversity variables (EBVs) are a minimum set (20) of measurements, conceptually located between low-level primary observations and high-level biodiversity indicators , to capture major dimensions of biodiversity change (Pereira et al., 2013).	Examples of EBV data products are available from the GEOBON EBV data portal (https://portal.geobon.org). An example is the 'Forest loss year (2000-2018)' product as an ecosystem distribution EBV (in the 'Ecosystem structure' EBV class).

2.1 Filtering of post-2020 goals and targets

We used a filtering approach (Figure 1) to include only those goals, targets and target components which capture the state of terrestrial biodiversity and potentially are observable from space (see Supplementary Materials S1). For this, we classified keywords (Table 2) within the textual descriptions of the monitoring elements from the zero draft, as these descriptions define the monitoring focus for the target components. We then updated this with the updated descriptions of goals, targets and target components from the 1st draft (CBD, 2021), because monitoring elements are no longer mentioned in the 1st draft. Additionally, some target components had been removed, others had been modified, and some new ones had been added (see details in Supplementary Material S2).

Table 2 Classification of textual descriptions in the zero draft and 1st draft of the post-2020 global biodiversity framework in terms of monitoring type (remotely observable characteristics, genetic resources, management policies), habitat (aquatic, terrestrial, agnostic), and DPSIR classes (driver, pressure, status, impact and response). Descriptions (keywords) from monitoring elements associated to specific goals and targets (*n* = 162) were assigned to a particular class.

Classes	Text descriptions (keywords)	*n*	Included
Monitoring type			
Remotely observable characteristics	area, aquatic, degradation, extent, fauna, flora, fragmentation, marine, plants, quantity, quality, rate of change, reduction, species, terrestrial, wilderness	109	Yes
Genetic resources	biotechnology, genetic, breed	6	No
Management policies	accounts, awareness, capacity-building, consumption, cooperation, economy, education, financial resources, funding, knowledge, participation, policies, private, public, regulations, rights, strategy, subsidies, technology transfer, women, youth, planning levels	47	No
Habitat			
Aquatic	aquaculture, aquatic, coastal, coral reefs, fish, fisheries, fresh water, mangroves, marine, sea grass, wetlands,	23	No
Terrestrial	agriculture, farmland, forest, grassland, islands, land, terrestrial, wilderness,	45	Yes
Agnostic	alien invasive species, climate change mitigation, natural ecosystems	41	Yes
DPSIR classes			
Driver	agriculture, harvest, quota, trade, access	11	No
Pressure	conflicts, extinction, pollution	15	No
State	area, connectivity, extent, quality	33	Yes
Impact	contributions to human, impacts, well being	9	No
Response	control, eradication (of invasive species), management, measures, practices, recovery, sustainable	18	No

We included only those elements that can potentially be observed with SRS (*n* = 109) and excluded those associated with 'genetic resources' (*n* = 6) and 'management policies' (*n* = 47) (Table 2). Afterwards, we classified the remaining monitoring elements (*n* = 109) with respect to habitat and only included non-aquatic elements. Finally, we selected those elements that capture the state of biodiversity (Table 1), as EBVs are defined as state variables. Classifying each monitoring element into the Driver-Pressure-State-Impact-Response (DPSIR) framework (Burkhard and Müller, 2008) identified 33 elements for the state of biodiversity (Table 2), spread across two goals (A & B), six targets and 17 target components (see Supplementary Material S1).

2.2 Biodiversity indicator workflow analysis

From the list of indicators associated to these goals, targets, and target components (see Supplementary Material S3 Table S3.1) we identified 50 unique indicators that focus on monitoring the state of terrestrial biodiversity. For each indicator, described in scientific publications, technical reports, and websites (sources in Table S3.3 in Supplementary Material S3), we performed an in-depth analysis of the workflows and collated details on the spatial information products underlying them (see Table S4.1 in Supplementary Material S4). In this step, we did not distinguish between products acquired from SRS and those acquired by other means if spatial information had been used in the creation of the product.

The spatial information products were then sorted into the EBV classification (Figure 1), using the updated version of the EBV list from GEO BON (https://geobon.org/ebvs/what-are-ebvs/), that differentiates 20 EBVs in six EBV classes. For instance, the ESA Landcover CCI data product was grouped into the live cover fraction EBV and the 'Terrestrial Ecoregions of the World' (Sayre et al., 2020) into the ecosystem distribution EBV. This provided us how often EBVs and EBV classes are represented by the different biodiversity indicators (full details provided in Supplementary Material S4).

Table 3 Criteria used for ranking satellite remote sensing products in the context of the post-2020 global biodiversity framework. The definitions for the feasibility, accuracy and (im)maturity criteria correspond to those used by an expert assessment (Skidmore et al. 2021), with the exception that we used the inverse definition of maturity (= immaturity) to focus on the potential of (upcoming) remote sensing techniques. The relevance was defined and quantified in our study, i.e. in the context of how essential biodiversity variables (EBVs) derived from satellite remote sensing could contribute to the post-2020 goals and targets (see methods).

Criteria	Description	Ranking (good = 1)	Ranking (poor = 3)
Relevance	A measure of how EBVs derived from satellite remote sensing could contribute to the CBD 2030 targets.	$= \begin{cases} 1 \; for \; EBV_{usage} > 10 \\ 2 \; for \; EBV_{usage} > 1 \; \& \; EBV_{usage} \leq 10 \\ 3 \; for \; EBV_{usage} \leq 1 \end{cases}$	
Feasibility	The science community knows how to measure the remote sensing biodiversity product at appropriate scales that such measurements can realistically be made and/or that observations already exist	Indicates the maturity of science/ technology/ experience needed to make the remote sensing biodiversity product	Indicates that considerable research and development effort remains or that remote sensing biodiversity products at the scale needed are technically, logistically or financially difficult to make
Accuracy	A measure of the accurate observation of a given remote sensing variable. It considers the effectiveness of remote sensing data and techniques to achieve an accurate and precise value of the remote sensing enabled biodiversity variable.	Fully operational network or service is in place, generating remote sensing biodiversity products that are accurate for the purpose	Indicates that no or very limited action has been taken to generate accurate remote sensing biodiversity products

Immaturity	The potential of developing remote sensing biodiversity products can be identified and/or proposed to a funding body	Indicates that at present a relevant infrastructure for the remote sensing variable is absent and consequently still has a high potential to be operationally produced.	Indicates the remote sensing variable is mature (with little development steps required) and is operationally produced within a relevant infrastructure

2.3 EBV usage and ranking

The final step of the top-down review was the counting of EBV usage (Figure 1), i.e., to calculate how often EBVs were used for each goal and target. We used a natural breaks classification to classify the usage into three ranks (rank 1 for a usage >10, rank 2 for a usage >1 and rank 3 for usages ≤1). This allowed us to be consistent with the three-point scoring system used by Skidmore et al. (2021) for the other criteria.

For the ranking of EBV information (Figure 1) we used the relevance, feasibility, accuracy, and immaturity criteria (Table 3). In contrast to the expert assessment of Skidmore et al. (2021) which aimed to provide a priority list for space agencies, our aim was to identify which SRS-enabled EBV workflows could be developed by the scientific community, to expand the tracking of CBD goals and targets. We therefore adapted the results from Skidmore et al. (2021) in the following way (overview in Table 3). First, we used our relevance score (see above) to explicitly focus on the relevance for CBD goals and targets. Second, we utilized the feasibility, accuracy and maturity scores as provided by Skidmore et al. (2021), except that we defined immaturity as the inverse of the maturity score to highlight the potential of (upcoming) SRS techniques rather than those that are currently already operational. By combining the scores of the four criteria we created a priority list which ranked the potential of SRS products to contribute to the biodiversity indicators in the form of EBVs.

2.4 Assessing the consequences of a priority selection

We analysed the consequences of focusing only on the top SRS products of the priority list (Figure 1), i.e., developing EBV workflows only for those SRS products that have the highest priority rather than the full list of all products. We therefore calculated the relative EBV coverage, i.e., counting the total usage of EBVs for each goal and target (Table 4) and comparing it to the usage of EBVs appearing in the top selection. This allowed us to investigate how the development effort (i.e., EBV coverage for monitoring target components) would be reduced when focusing only on the top priority selection.

3 Results

3.1 Filtering of post-2020 goals and targets

We identified a total of 35 monitoring elements from the zero draft of the post-2020 global biodiversity framework to track the state of terrestrial biodiversity with spatial information products (details in Table S1.1 in Supplementary Material S1). This represented two CBD goals, seven targets and sixteen target components (Table 4), of which targets 1, 2, 3, 6 and 8 aimed at goal A and target 10 and 11 at goal B. None of the targets in goals C and D focused on monitoring the state of terrestrial biodiversity with SRS observations. For the identified goals and targets, we found a combined usage of 59 biodiversity indicators, spread over goal A (n = 26) and goal B (n = 3) and specific targets (n = 31) (see Table S3.1 in Supplementary Materials S3). We also found that some indicators are used multiple times within different goals and targets, such as the Bioclimatic Ecosystem Resilience Index (2×) and the Species Protection Index (3×), leading to a total of 50 unique indicators.

Table 4: Goals and target components of the 1st draft of the post-2020 global biodiversity framework that track the state of terrestrial biodiversity. The 17 target components are spread over six targets and two goals (A, B) and were identified by analysing the descriptions of all monitoring elements in the zero draft of the post-2020 global biodiversity framework (see methods and Figure2) and updated with the 1st draft of the post-2020 global biodiversity framework.

Goals	ID	Description
Goal A: Reducing threats	A.1	Area of natural ecosystems
	A.2	Connectivity of natural ecosystems
	A.3	Integrity of natural ecosystems
	A.4	Abundance and distribution of populations of species
	A.5	Species extinction rate
	A.6	Species extinction risk
	A.7	Proportion of species that are threatened
	T1.1	Area under integrated biodiversity-inclusive spatial planning
	T1.2	Retention of existing intact and wilderness areas
	T2.1	Area of freshwater, marine and terrestrial ecosystems restored
	T2.1	Connectivity
	T3.1	Area protected and conserved
	T3.2	Areas of particular importance for biodiversity protected and conserved
	T3.4	Connectivity within the system of protected areas and other effective area-based conservation measures
	T6.1	Effective detection, identification, prioritisation and monitoring of invasive alien species
	T6.2	Control or eradicate invasive alien species
	T6.3	Reducing the impact on priority species and priority sites
	T8.1	Minimize impact of climate change
	T8.3	Ensure that all mitigation and adaptation efforts avoid negative impacts on biodiversity
Goal B: Meeting Peoples Needs	B.1	Nature and its contributions to people are fully accounted and inform all relevant public and private decisions
	B.2	Long-term sustainability of nature's contributions to people is ensured
	B.3	Nature's contributions to people in decline restored
	B.4	Contribution to other relevant Sustainable Development Goals
	T10.1	Agriculture
	T10.3	Forestry
	T11.1	Regulation of air quality
	T11.2	Regulation of hazards and extreme events

3.2 Biodiversity indicator workflow analysis

Of the 50 biodiversity indicators, 28 provided sufficient information on their workflows (details in Table S3.3 in Supplementary Material S3). For 7 indicators, workflows were not traceable (see Table S3.2 in Supplementary Material S3), and for 15 workflows were (at the time of our analysis) still in development. From the 28 biodiversity indicator workflows, we identified 53 unique variables which relied on spatial information products (details in Table S4.1 in Supplementary Material S4). Example of SRS products include the Global Forest Change product (Hansen et al., 2013) provided by Global Forest Watch and the CCI landcover product (ESA, 2017) produced by the European space agency (ESA). Each variable was then classified into one of the 20 EBVs (detailed overview in Supplementary Material S4).

3.3 EBV usage and ranking

The indicators most often used spatial information products associated with the EBV classes 'species populations' and 'ecosystem structure' (Figure 3). EBVs in the classes 'community composition' and 'ecosystem functioning' were moderately represented (Figure 3). The 'species traits' and 'genetic composition' EBV classes were not represented (Figure 3).

Within the 'ecosystem structure' EBV class, the highest usage was related to the life cover fraction and ecosystem distribution EBVs (Figure 3). Within the 'species populations' EBV class, all spatial information products were related to the species distributions EBV rather than to the species abundances EBV (Figure 3). The high usage of EBVs (e.g., life cover fraction, ecosystem distribution, and species distributions) resulted in a high relevance score (= 1). EBVs that were not used by biodiversity indicator (e.g., ecosystem vertical profile and species abundances) were given a low relevance score (= 3). EBVs with intermediate use (e.g., primary

production and ecosystem disturbance in the EBV class 'ecosystem functioning') were given a moderate relevance score (= 2).

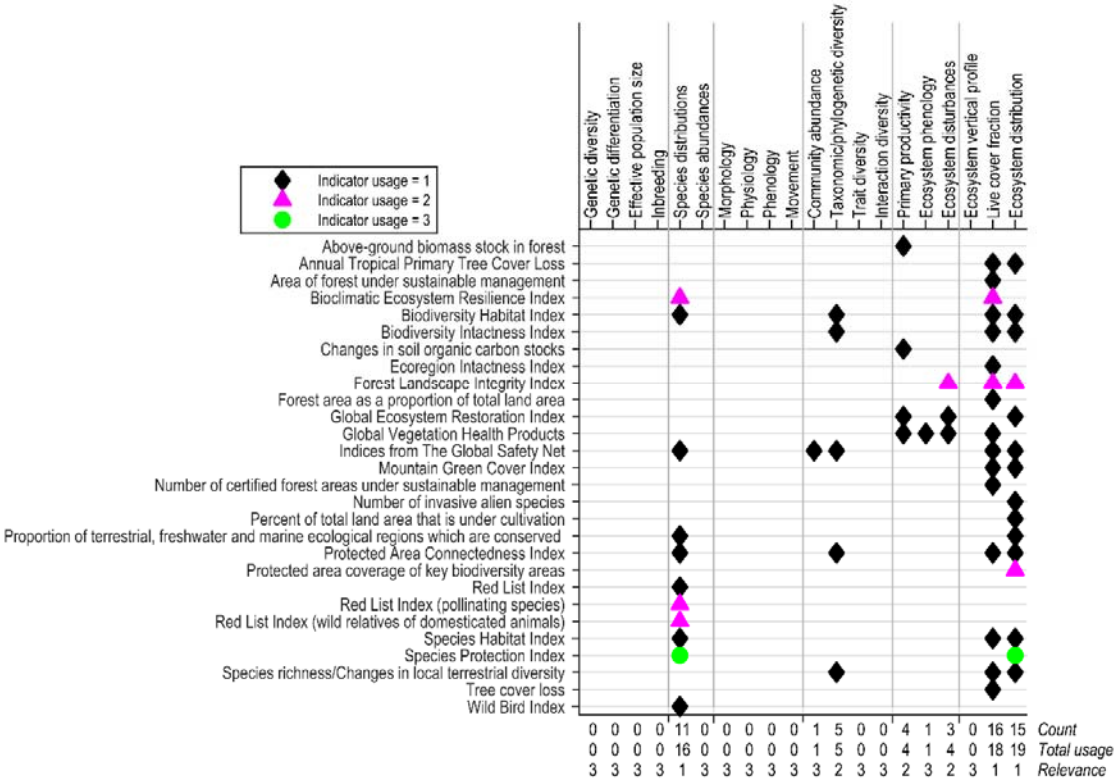

Fig. 3. Biodiversity indicators and their underlying data sources categorised into essential biodiversity variables (EBVs). The indicators (y-axis) represent those that are listed in the post-2020 global biodiversity framework for those goals and targets that focus on tracking the state of terrestrial biodiversity. As some biodiversity indicators (e.g. the Species Protection Index) are used in multiple goals and targets, the total usage of the underlying EBVs (such as species distributions or ecosystem distribution) can be larger than the count, resulting in a higher relevance score in the ranking (see Table 3). Symbol colours reflect how often an indicator is used (black diamonds = 1, purple triangles = 2, green circles = 3).

Relevance scores were combined with feasibility, accuracy, and immaturity scores to derive an overall ranking of SRS products and their associated EBVs (Table S5.1 in Supplementary Material S5). The SRS products in top priority list (Table 5) with the highest rank (total score = 6) were fraction of vegetation cover and plant area index profile with the highest rank (total score = 6), followed by above-ground biomass, foliar N/P/K content, land cover (vegetation type) and leaf area index (total score = 6.5). Five additional SRS products were also included in the top priority list (total score = 7, see Table 5), namely carbon cycle biomass (above-ground biomass), chlorophyll content and flux, ecosystem fragmentation, ecosystem structural variance, and gross primary productivity.

3.4 Assessing the consequences of a priority selection

The full list of spatial information products showed a diverse coverage of EBVs, especially in goal A and its related targets T1–T3, T6 and T8 (Figure 4a). Most products were associated with the EBVs species distributions, live cover fraction and ecosystem distribution (Figure 4a). When reducing development efforts to those EBVs from the top priority list, the relative coverage across the goals and targets remained similar, but the tracking was reduced (Figure 4b).

Table 5 Priority list of satellite remote sensing products for monitoring the state of terrestrial biodiversity in the context of the post-2020 global biodiversity framework. Each product is grouped into the Essential Biodiversity Variable (EBV) framework as defined by the Group on Earth Observations Biodiversity Observation Network. The scores of feasibility, accuracy and immaturity (inverse of maturity) were obtained from Skidmore et al. (2021), whereas the scores for relevance were derived in this paper (see methods). See Supplementary material S5 Table S5.1 for the full list of satellite remote sensing products and rankings).

Remote sensing biodiversity product	EBV	Scoring					Rank
		Feasibility	Accuracy	Relevance	Immaturity	Total	
Fraction of vegetation cover	Live cover fraction	1	2	1	2	6	1
Plant area index profile	Live cover fraction	1	2	1	2	6	1
Above-ground biomass	Ecosystem distribution	1.5	1	2	2	6.5	3
Foliar N/P/K content	Primary productivity	1.5	1	2	2	6.5	3
Land cover (vegetation type)	Live cover fraction	1	1.5	1	3	6.5	3
Leaf area index	Physiology	1	1.5	3	1	6.5	3
Carbon cycle (above-ground biomass)	Primary productivity	1	2	2	2	7	7
Chlorophyll content and flux	Physiology	1	2	3	1	7	7
Ecosystem fragmentation	Ecosystem distribution	1	2	2	2	7	7
Ecosystem structural variance	Ecosystem distribution	1	2	2	2	7	7
Gross primary productivity	Physiology	1	2	3	1	7	7
	Average	1.09	1.73	2.00	1.82		
	Standard deviation	0.20	0.41	0.77	0.60		

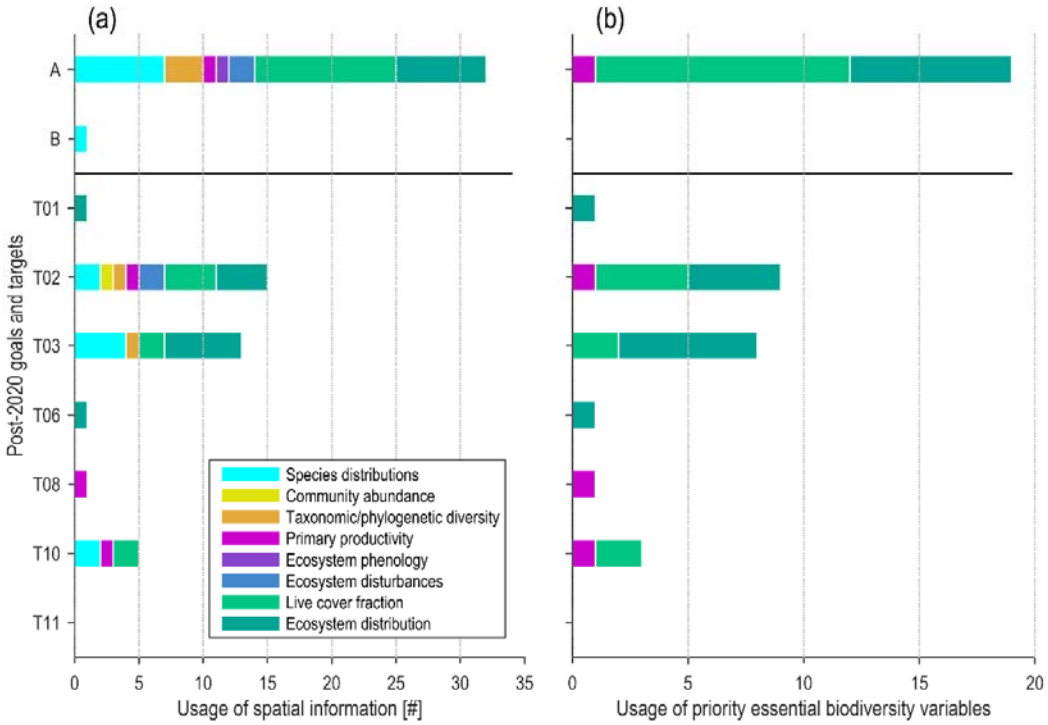

Fig. 4. Usage of spatial information products and associated essential biodiversity variables (EBVs) within the 2030 goals and targets of the post-2020 global biodiversity framework. (a) Total usage of spatial information products coloured by EBV. (b) Representation of EBVs in the top priority list (Table 5) of satellite remote sensing products. Note that no spatial information product could be identified for target 11 because the available biodiversity indicators did not focus on the state of terrestrial biodiversity (our inclusion criteria).

4 Discussion

By integrating biodiversity indicator information from the post-2020 global biodiversity framework with expert assessments of satellite products we identified scientific opportunities for developing SRS-enabled EBV workflows. We ranked and prioritized SRS products in terms of their policy relevance and their potential for EBV development regarding feasibility, accuracy, and immaturity. Our analysis revealed that SRS products associated with ecosystem distribution and live cover fraction are both highly relevant in the CBD context and highly ranked for future development. In contrast, SRS products related to plant physiology and primary productivity (e.g., leaf area index, chlorophyll content & flux, and foliar N/P/K content) remain under-used but are ranked highly, thereby unveiling promising opportunities for developing new EBV workflows from SRS. Below we discuss specific actions to capitalize on these opportunities.

The most widely used spatial information products in the analysed workflows were associated with the EBVs ecosystem distribution, live cover fraction and species distributions. Some of the SRS products associated with the ecosystem distribution EBV, e.g. the Global Forest Change product (Hansen et al., 2013), have already been mobilized into the EBV Data Portal of GEO BON (https://portal.geobon.org/home). However, the identified products are diverse and often used widely across multiple biodiversity indicators. Many products are related to land use, but with strong differences in the underlying methodology, e.g. in radiometric correction, classification, and legend information (Herold et al., 2008). This can lead to inconsistencies and uncertainties in biodiversity indicators (Martin et al., 2019; Tuanmu and Jetz, 2014) and thereby affect the tracking of policy goals and targets. Hence, more consistent, and harmonized ecosystem distribution products need to be developed that are scalable and universally applicable. Already harmonization projects exist, e.g. in the context of climate change modelling (Hurtt et al., 2020). However, land use information often remains too coarse (e.g. 1 km resolution) for ecological applications, and many biodiversity indicators would require fine spatial resolutions (e.g. 10–30 m), e.g. the Species Protection Index (GEO BON, 2015) or the Bioclimatic Ecosystem Resilience Index (Ferrier et al., 2020). While higher resolution products exist, e.g. GlobLand30 (Chen et al., 2015), their ecological and thematic detail is still insufficient and inappropriate for tracking changes in ecosystem distribution in a policy context. For instance, monitoring ecosystems for the EUNIS habitat types in the context of the EU Habitat Directive requires data on plant community composition from vegetation plots to be integrated with satellite-based information on land cover, vegetation phenology and productivity (Pereira et al., 2022). Hence, SRS needs to develop better (harmonized and high resolution) products of ecosystem distribution for policy applications.

Spatial information products associated with the live cover fraction EBV were also diverse and included various measures of fractional cover such as vegetation fraction from MODIS (DiMiceli et al., 2017) and fractional land cover patterns (Hurtt et al., 2020). These products are frequently used in workflows to characterize ecosystem quality (Venter et al., 2016), ecosystem integrity (Grantham et al., 2020) and habitat intactness (GEO BON, 2015). The potential of SRS to estimate life cover fraction has been widely recognised (Gao et al., 2020; Skidmore et al., 2015; Valbuena et al., 2020; Vihervaara et al., 2017), but such products have not yet been mobilized into the EBV Data Portal of GEO BON. One reason might be that the development of life cover fraction EBVs requires to define a taxonomy of ecosystems and how the fraction of each vegetation (or plant functional) type relates to a desired baseline, i.e., an ecosystem reference state. Most SRS products of fractional cover, such as the ESA CCI product (ESA, 2017), have been developed in the context of specific land use for climate change modelling and show rather coarse classifications that are not detailed enough for defining policy-relevant ecosystems. Therefore, it largely remains unexplored what the desired state of fractional cover (e.g. of trees, shrubs, grasses or other life forms) will be for the different taxonomies of the

terrestrial ecoregions of the world (Olson et al., 2001) or the EUNIS terrestrial habitat classification of the European Union (Davies et al., 2004; EEA, 2014). Development of life cover fraction EBVs will therefore benefit from closer collaborations between SRS experts, ecologists and policy-makers (Pettorelli et al., 2016). Required are products of life cover fraction that are targeted towards policy-relevant ecosystems and allow comparison to a baseline fractional cover.

Many spatial information products within the analysed workflows were associated with the species distribution EBV, indicating its relevance in the CBD context. Such products were related to occurrence records, geographic range maps or data from bird surveys (Table S4.1 in Supplementary Material S4). These products, e.g. the Global Safety Net layers (Dinerstein et al., 2020), allow for the monitoring of rare, threatened and range-restricted species and areas of particular conservation importance. This is particularly relevant for CBD goal A which aims to reduce the rate of species extinctions. In this context, SRS is only rarely used because the spatial resolution of openly accessible products is not high enough for individual species detection (Damijanić, 2021). While classifications of native and invasive plant species in tropical forests (Asner et al., 2017; Somers and Asner, 2013) have been performed with imaging spectroscopy data, these applications have usually been based on airborne (rather than spaceborne) observations. Hence, opportunities for using current SRS observations in species distribution EBVs are mainly related to providing co-variates in species distributions models (Randin et al., 2020) rather than detecting species directly from space. This allows upscaling of ground-based species observations to a spatially contiguous extent (Dinerstein et al., 2020; Pinto-Ledezma and Cavender-Bares, 2020), e.g. by using land cover maps (Tuanmu and Jetz, 2014) or canopy tree height derived from LiDAR and RADAR (Alonzo et al., 2014; Van Ewijk et al., 2014). As new spaceborne hyperspectral instruments become available, species distribution monitoring from space will become increasingly common and viable, especially for monitoring plant species that dominate specific vegetation types.

In addition to the above-mentioned opportunities, observations from SRS also provide opportunities for developing new workflows (Reddy et al., 2021). To emphasize these opportunities for the scientific community (Bates and Privette, 2012; Bojinski and Richter, 2010), rather than emphasizing the maintenance of current missions by space agencies (Skidmore et al., 2021), we used the immaturity criteria which revealed a high priority of SRS products related to plant physiology and primary productivity. Specifically, plant physiology EBVs such as leaf area index, chlorophyll content and flux, and gross primary productivity, and primary productivity EBVs such as foliar N/P/K content and carbon cycle (above-ground biomass) ranked particularly high. Such species traits can provide essential information for tracking biodiversity change, including plant phenology (e.g. timing of flowering and fruiting) and stoichiometry (e.g. the balance between carbon, nitrogen and phosphorus) (Kissling et al., 2018). In addition, information regarding (canopy and leaf) trait dissimilarities (e.g. leaf area index, chlorophyll and foliar nitrogen) allows for discriminating the presence of alien invasive species (Große-Stoltenberg et al., 2016; Niphadkar and Nagendra, 2016) and together with ecosystem performance information (e.g. carbon cycle) allows for assessing their impact on ecosystem functioning, e.g., productivity (Große-Stoltenberg et al., 2018), nutrient cycling (Kumar and Garkoti, 2021) and energy exchange (Musavi et al., 2015). However, satellite observations are often too coarse (≥ 20m) in their spatial resolution for detecting individual species (Kissling et al. 2018; Skidmore et al., 2021). While satellites with higher spatial resolutions (<2m) exist, such as Superview and Worldview, they have limited temporal and spectral capabilities which currently prohibits the estimation of physiological plant traits. One promising opportunity would be to merge multiple satellite observations for estimating species traits EBVs. For instance, deep-learning techniques such as DeepForest can be applied to map individual tree species (Weinstein et al., 2020), and 3D models such as DART (Gastellu-Etchegorry et al., 2004) can be used to link plant heterogeneity to the radiative transfer (Widlowski et al., 2013). Finally, multi-sensor frameworks (Chernetskiy et al., 2017; Lewis et al., 2012) and data science techniques, such as model emulators (Gómez-Dans et al., 2016; Verrelst et al., 2012) and neural networks (Baret et al., 2013), would allow to integrate the above-mentioned components into consistent products of species traits. This would allow the disaggregation of leaf area index and chlorophyll and nitrogen content information to individual plants (Berger et al., 2020; Brede et al., 2020), which in turn could refine phenology assessments, improve stoichiometry characterisations and allow for more detailed alien invasive species discrimination.

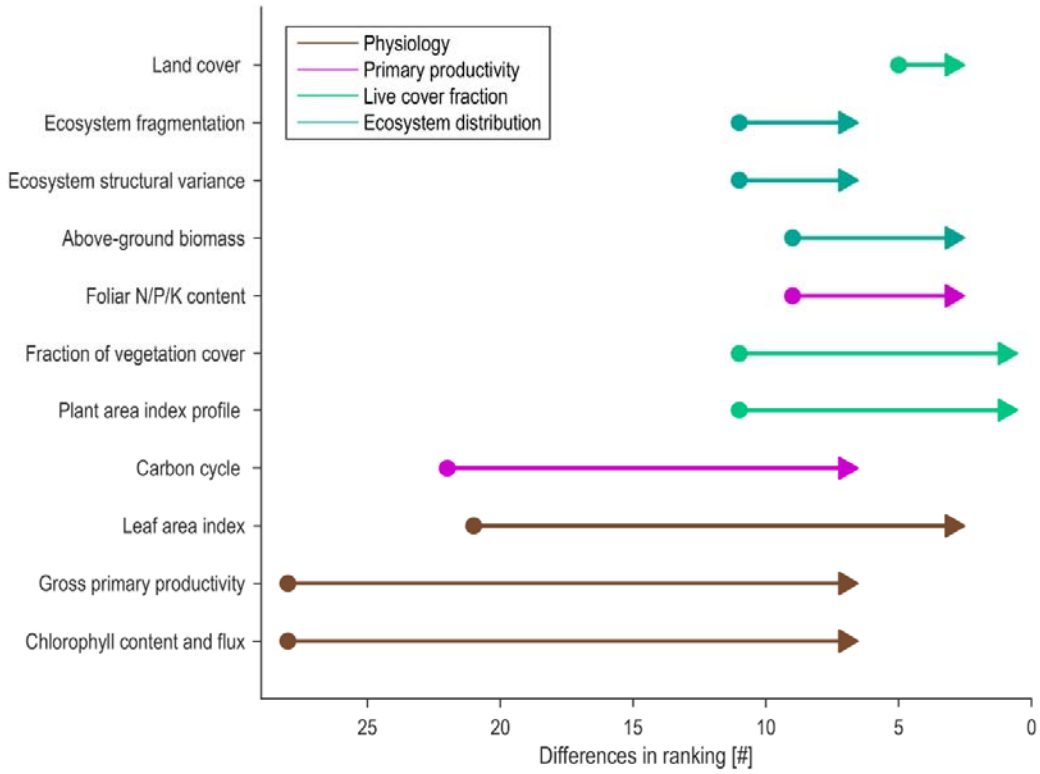

Fig. 5. Changes in the ranking of satellite remote sensing products from the top priority list (Table 5) when the innovation potential of workflow development by the scientific community (our focus) is compared to the operation and maintenance of missions by space agencies (focus of Skidmore et al. 2021). The difference in ranking (length of arrows) illustrates the change in rank of a specific product from the assessment by Skidmore et al. (2021) (represented with closed circles) to our assessment (represented by the arrow symbol). A lower rank represents a higher priority.

The opportunities highlighted above for developing SRS-enabled EBV workflows could make important contributions to the CBD goals and targets. Specifically, developing EBVs for ecosystem distribution and live cover fraction could enhance the tracking of target 2 ('connectivity of priority terrestrial ecosystems under restoration') and target 3 ('effective and equitable management of protected areas'). Likewise, EBVs for ecosystem distribution and live cover fraction that are closely linked to animal habitat requirements could lead to improvements for tracking goal A ('reducing species extinction rates'). Furthermore, building EBVs of primary production and plant species physiology would contribute to the tracking of target 5 ('pathways for the introduction and impact of invasive alien species') as well as target 10 ('increasing simultaneously the productivity and sustainability of agricultural and forested ecosystems'). Given the capabilities of new satellites, such as new imagers and higher spatial resolutions (Sadeh et al., 2021), and the integration of satellite observations with in situ data collection from field sampling, SRS will likely transform the tracking and monitoring of life on Earth if such data can be consistently integrated (Cavender-Bares et al., 2022; Pasetto et al., 2018).

5 Conclusion

The post-2020 global biodiversity framework is a major step forward in defining SMART (i.e. specific, measurable, achievable, relevant, and time-bound) targets (Butchart et al., 2016; Xu et al., 2021). Our integrated user-requirement analysis revealed exciting scientific opportunities for developing SRS-enabled EBV

workflows and indicators for tracking global biodiversity change in the CBD context. Major collaborative efforts between policy, ecology and remote sensing are needed to enhance the consistency, specificity and thematic content of SRS products associated with ecosystem structure EBVs, and to create multi-sensor frameworks for integrating and fusing different remote sensing observations for using species traits in ecological and policy applications. This will advance the tracking of policy goals and targets and contribute to reducing threats to biodiversity while meeting people's needs through the sustainable use of biodiversity.

6 CRediT authorship contribution statement

Joris Timmermans: Conceptualization, Methodology, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization.

W. Daniel Kissling: Conceptualization, Formal analysis, Validation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Funding acquisition.

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