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Priority list of biodiversity metrics to observe from space

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Monitoring global biodiversity from space through remotely sensing geospatial patterns has high potential to add to our knowledge acquired by field observation. Although a framework of essential biodiversity variables (EBVs) is emerging for monitoring biodiversity, its poor alignment with remote sensing products hinders interpolation between field observations. This study compiles a comprehensive, prioritized list of remote sensing biodiversity products that can further improve the monitoring of geospatial biodiversity patterns, enhancing the EBV framework and its applicability. The ecosystem structure and ecosystem function EBV classes, which capture the biological effects of disturbance as well as habitat structure, are shown by an expert review process to be the most relevant, feasible, accurate and mature for direct monitoring of biodiversity from satellites. Biodiversity products that require satellite remote sensing of a finer resolution that is still under development are given lower priority (for example, for the EBV class species traits). Some EBVs are not directly measurable by remote sensing from space, specifically the EBV class genetic composition. Linking remote sensing products to EBVs will accelerate product generation, improving reporting on the state of biodiversity from local to global scales.

Biodiversity encompasses the complex variety of life at all scales, ranging from genes to species to ecosystems. It encapsulates the structure, function, distribution, traits and composition of all living things. Crisis-level losses of biodiversity are stimulating action from local to global scales, as evidenced by establishment of the United Nations Sustainable Development Goals (SDGs) and Aichi targets and the current post-2020 negotiation of the Convention on Biological Diversity (CBD), as well as the first round of risk assessments by the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES)[1]. In response to these losses of biodiversity, the Group on Earth Observations Biodiversity Observation Network (GEO BON)[2,3] proposes a common framework of essential biodiversity variables (EBVs)[4] for monitoring biodiversity. These EBVs form a core set of complementary biological measurements for capturing considerable biodiversity change and are produced by

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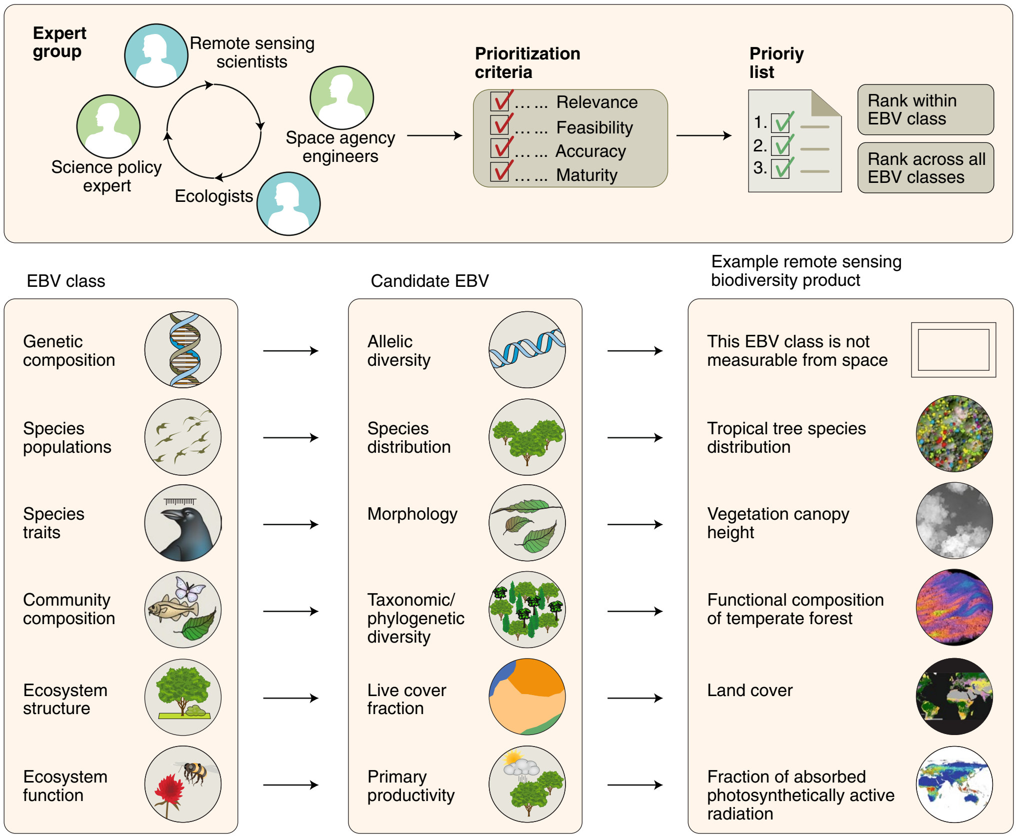


Fig. 1 | Ranking and scoring approach for example remote sensing products. Tropical tree species distribution image adapted from ref. [18] under a Creative Commons license CC BY 4.0; vegetation canopy height image adapted with permission from ref. [25], Elsevier; functional composition of temperate forest image adapted from ref. [46] under a Creative Commons license CC BY 4.0; land cover image adapted from ref. [34] under a Creative Commons license CC BY 4.0; fraction of absorbed photosynthetically active radiation image adapted from ref. [27], Copernicus Global Land Service (contains modified Copernicus Service information [2020]).

integrating primary observations from in situ monitoring with remote sensing.

Biodiversity change occurs at a range of spatial and temporal scales[5]. Many biodiversity-relevant measures may be retrieved from remote sensing (airborne and satellite), including measures of change in ecosystem structure and function, community composition, species traits and species populations (Fig. 1). As such, current and emerging next-generation satellite remote sensing is an ideal tool for the continuous detection of changes in biodiversity from local to global levels, thereby filling data gaps in the spatial and temporal coverage of in situ observations. To date, however, there has been little exploration on how to bridge the work of ecologists (who address the efficacy of using EBVs for biodiversity monitoring) and remote sensing specialists (who address technologies deriving remote sensing products related to EBVs). Particularly lacking is a focus on the technical requirements needed to ensure that EBVs are operationally realistic from a remote sensing perspective. We therefore define remote sensing biodiversity products as outputs derived from the processing of remotely sensed images that closely inform EBVs.

Development of the specifications for sensors is normally undertaken by staff at space agencies, who consult widely to decide on priorities for the upcoming decades. Space agencies then require engineers to design satellite sensors under strict requirements that affect factors such as temporal and spatial resolution, signal-to-noise ratios and other design considerations. As a result, it may be entirely unrealistic to monitor EBVs that are highly relied on by the ecological community from space. This Perspective considers the EBV concept and remote sensing-enabled biodiversity products to provide context to space agencies and remote sensing developers. Likewise, we clarify for ecologists which EBVs are feasible to measure with remote sensing and at what scales.

Monitoring EBVs over large areas from space-based platforms will require discussion between ecologists, space agency engineers and remote sensing experts to ensure that remote sensing satellites are being developed to meet the global need for biodiversity data[4,6,7]. Remote sensing engineers emphasize the need for processing chains that have open, accurate, repeatable and reproducible workflows for the sake of consistent and long-term monitoring of biodiversity. Scientists and engineers agree that there is a need to build a globally coordinated, scientifically rigorous programme following the findable, accessible, interoperable and reusable data principles[8], in order to track how global biodiversity is changing. A global monitoring system can only be achieved by combining satellite remote sensing with in situ observations in a cost-effective, consistent, accurate and coordinated manner.

In this Perspective, we focus on biodiversity measures from satellite Earth observation data, which may be developed in the next decade using current and planned assets of the space agencies. We do not consider other remote sensing technologies (such as airborne, unmanned aerial vehicle and terrestrial sensors), since we seek to evaluate datasets that offer synoptic (regional to near-global) coverage with pre-defined temporal lags. Rather, we prioritize EBV-related remote sensing biodiversity products that are biological, sensitive to short- to medium-term change, spatially scalable, as conceptually generalizable as possible across the terrestrial,

Table 1 | Remote sensing biodiversity product prioritization criteria and ranking factors

Prioritization criteria	Description	Ranking = 1 (good)	Ranking = 3 (poor)
Relevance	It is known who wants the remote sensing biodiversity product, what they will do with it and how it will be used. The remote sensing biodiversity product is relevant: (1) for management questions; (2) to inform the CBD targets; (3) to inform the SDG(s); and (4) to provide data for the IPBES risk assessment processes.	Use and user fully identified.	Remote sensing biodiversity product less directly linked to science and societal questions.
Feasibility	The science community knows how to measure the remote sensing biodiversity product at such scales that measurements can realistically be made and/or observations already exist. This criterion considers the availability of remote sensing data, the ease of access to such data, the completeness of remote sensing in space and time and the ease and affordability of data integration and analysis.	Indicates maturity of the science, technology and experience needed to make the remote sensing biodiversity product.	Indicates that considerable research and development effort remains or that remote sensing biodiversity products on the scale needed are technically, logistically or financially difficult to make.
Remote sensing status: accuracy	A measure of the current activity for the accurate observation of a given remote sensing biodiversity product. This criterion considers the effectiveness of remote sensing data and techniques to achieve an accurate and precise value of the remote sensing-enabled biodiversity product.	A 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.
Remote sensing status: maturity	Institutions/organizations with hopes to generate remote sensing biodiversity products can be identified and/or proposed to a funding body.	Operationally implemented with satellite remote sensing. It is known who needs to act and what action needs to be taken so that the remote sensing biodiversity product can now be produced.	Indicates a complete lack of relevant infrastructure or relevant implementation organizations that would allow a remote sensing biodiversity product to be conceivably produced from satellites within the next decade.

freshwater and marine realms[4] and feasible given the expected development of remote sensing satellites (Fig. 1). When translating an EBV to biodiversity product(s) measured from a satellite, the remote sensing biodiversity product will constrain the EBV into a fixed grid (such as a 16-d revisit time or a 30-pixel resolution)[9,10], necessitating the integration of various sources of satellite imagery. We hope to stimulate discussions between space agencies, the science community, government and the private sector on integrating biodiversity measurements enabled by Earth observation, to help develop effective, high-level indicators to monitor change in biodiversity for policymakers and decision-makers[11,12] from local to global levels.

Our aim is to propose a priority list of currently available remote sensing biodiversity products that are both highly useful for end users (for example, CBD post-2020 targets, SDGs, IPBES, governments and other stakeholders, including companies and non-governmental organizations) and highly meaningful to data providers (for example, space agencies and those researching and generating remote sensing biodiversity products) to ensure continuous biodiversity measurements at relevant spectral, spatial and temporal scales. We emphasize that this is not a definitive priority list, but rather a call for action to provide a detailed assessment of the broad categories of biodiversity variables that can be monitored by remote sensing from space and can provide a framework for further developing satellite and ground assets.

A critical review of EBVs retrieved by remote sensing

Prioritizing remote sensing biodiversity products requires a critical overview of the link between EBVs and remote sensing products. We identified nearly 120 biodiversity products that provide critical information about biodiversity change and can be derived from satellite remote sensing. We then assessed and grouped these biodiversity products based on their similar abilities and approaches to supporting biodiversity monitoring through remote sensing. Many of these potential remote sensing biodiversity products had elements in common with the original EBVs[4] and EBV candidates from the GEO BON network[3], allowing the biodiversity products to be further grouped by EBV class and candidate EBVs.

In an iterative process, an original list of over 120 biodiversity-related variables and attributes was merged, culled and sorted into a list of remote sensing biodiversity products using a modified Delphi approach[13]. This merged list formed the basis for prioritizing the remote sensing biodiversity products (Table 1) using an adapted procedure (Figs. 2 and 3) first developed for prioritizing essential climate variables[14,15].

Following this methodology, a critical issue emerged: some biodiversity-related variables used in remote sensing do in fact differ from the EBVs listed by the GEO BON network (ref. [3] and N. Fernandez, in review). Supplementary Table 1 details the terminology that is typically used for remote sensing biodiversity products and the associated EBV (for EBV names that differ from the typical remote sensing variable names, the column 'Typical remote sensing-enabled biodiversity variables' shows the equivalent remote sensing term to describe biodiversity). Remote sensing-enabled biodiversity variables may diverge from EBVs because: (1) they may be constrained by sensor characteristics; and (2) the naming conventions and contents of some remote sensing-enabled biodiversity variables differ from those of similar EBVs. To reduce confusion around the use of EBVs and add order to commonly used terms in remote sensing, we translated between the variable names used in the GEO BON EBV list and typical remote sensing biodiversity products used in Earth observation (Supplementary Table 1).

The remote sensing biodiversity products were grouped, to harmonize the terminology used by the ecological and remote sensing communities. For example, a biodiversity variable widely

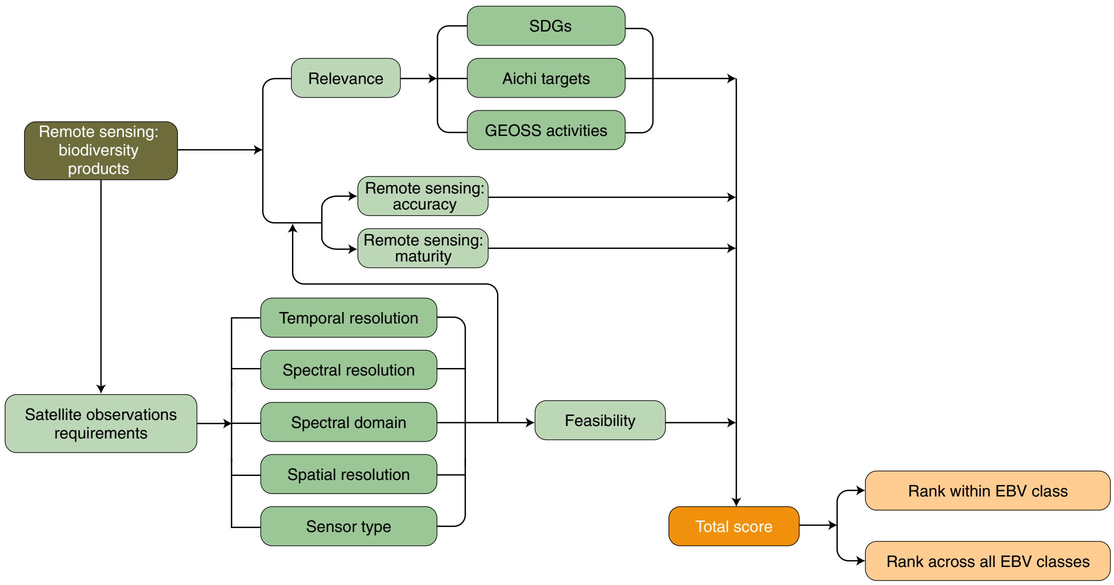


Fig. 2 | Flow chart for the scoring and ranking of remote sensing biodiversity products. Note that SDGs are the UN Sustainable Development Goals, Aichi targets refer to the Convention on Biological Diversity Aichi targets, and GEOSS is the Global Earth Observation System of Systems.

used in remote sensing is spatial configuration[16,17], describing the pattern and texture of patches at different ecological scales. This corresponds to the candidate EBV ecosystem distribution. As can be seen in Supplementary Table 1, multiple remote sensing biodiversity products such as forest species and age class[18,19] and population density[20] can estimate the original EBV species abundance. Furthermore, we noted that some EBVs listed by GEO BON, such as live cover fraction and ecosystem vertical profile, are often used analogously in remote sensing, typically being named habitat structure, and may be derivable from the same remote sensing biodiversity products (Supplementary Table 1).

Remote sensing biodiversity products such as the fraction of absorbed photosynthetically active radiation, leaf area index, net and gross primary production, foliar chemistry content, green-up (start of season) or vegetation height (see Supplementary Table 1) are example products derived directly from satellite remote sensing using physical models[21–27] to form continuous surfaces. Categorical, thematic or discrete remote sensing biodiversity products such as land cover and species abundance have definite feature boundaries for each category (or class), generated by models that combine remote sensing with ancillary (often abiotic) data, with a label describing the category (or class) often being (uniquely) defined by local ecological knowledge[28–31]. Consequently, continuous products are—from a software engineering perspective—more feasible for automatic global mapping and monitoring using remote sensing, as there is no need for thresholds and class labels to be assigned and modified by users[32,33]. Once a physical algorithm can describe a continuous surface, the remote sensing biodiversity product may be consistently generated for every satellite image over an extended time period using image processing pipelines such as the Copernicus Global Land Service[34]. In contrast, categorical products depend on specific training of in situ field data for each discrete category, which can be costly to calibrate, demands ecological knowledge and even requires agreement on how a discrete class should be labelled (for example, as a forest or woodland)[35–37]. It should be noted that hybrid categorical–continuous remote sensing products are being increasingly used. Hence, for example, the accuracy of continuous physical products such as net primary productivity and leaf area index (LAI) can be further improved by using land cover (a categorical product) as an input[38].

Finally, when harmonizing the terminology used by ecological and remote sensing communities, it is important to emphasize that utilizing broadband optical wavelengths (for example, for PlanetScope, approximately 60–90 nm) at very high spatial resolution (that is, 1–5 m) will not, by itself, retrieve biodiversity products more accurately. This is because different parts of the electromagnetic spectrum may be useful for retrieving specific biodiversity products (for example, plant biochemicals from the red edge and thermal infrared domain), while active sensors such as light detection and ranging (LiDAR) are immensely powerful for retrieving three-dimensional (3D) habitat structure, such as the EBV ecosystem vertical profile. Technical limitations often demand a trade-off between the spatial, spectral, radiometric and temporal resolution of imagery[39], as it is not possible for a single sensor to concurrently have a high spatial resolution, large numbers of narrow spectral bands covering the full spectrum range, and a high signal-to-noise ratio in a single sensor. This is termed the typical-length scale[40]. For instance, an individual tree, required for mapping the EBV classes species populations[18] and species traits, cannot be identified at the typical-length-scale spatial resolution of a Sentinel-2 or Landsat-7 and 8 image pixel, but may be feasible using a very-high-resolution image (for example, PlanetScope)[41], which could then be combined, or fused, with satellite hyperspectral imagery such as the (operational) Italian PRISMA and German DESIS and (planned) National Aeronautics and Space Administration (NASA) and European Space Agency satellites (SBG and CHIME). Fusing of data from these different (and emerging) sensor technologies allows remote sensing biodiversity products to be transformed into EBVs, and ultimately higher-level indicators, although an important caveat is that efficacious image fusion requires skilled image processing approaches[42].

Refining remote sensing biodiversity variables

Because the original EBV classes[4] are fully recognizable in several different remote sensing products at the highest level of EBV grouping, the original EBV classes became a key departure point. However, we identified the following key issues of incompatibility between EBVs and remote sensing that will need to be addressed to make the best use of remote sensing techniques in measuring biodiversity.

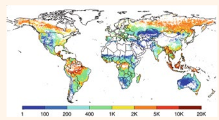
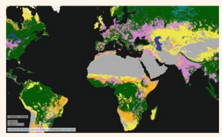
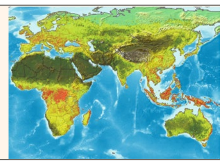
Remote sensing product		Ranking factor		Ranking across all EBV classes	Explanation
Biological effects of fire disturbance ($gC\,m^{-2}$)		Relevance	1	1	Highly relevant data layer widely used for protected area and land management, as well as informing about biodiversity for national and international reporting. Data are available in virtually real time. The data are accurate and the technology is mature.
		Feasibility	1		
		Accuracy	1		
		Maturity	1		
Land cover		Relevance	1	5	Highly relevant data layer widely used for ecological research and management, as well as moitoring biodiversity for national and international reporting. Data are available in virtually real time. The technology is mature but cover classes are subjective (for example,'define forest').
		Feasibility	1		
		Accuracy	1.5		
		Maturity	1		
FAPAR		Relevance	2	11	Interpreting FAPAR remains challenging for many managers and ecologists as its use as a biodiversity indicator is not fully established. Data are available in virtually real time. The technology is mature but calibration and validation of global FAPAR over time requires more in situ data.
		Feasibility	1		
		Accuracy	2		
		Maturity	1		

Fig. 3 | Example prioritization of three remote sensing biodiversity products. See Table 1 for definition of the ranking factors (that is, 1 = good, 3 = poor) and Supplementary Table 2 for merged remote sensing biodiversity products list and details of the expert ranking. Biological effects of fire disturbance image reproduced from ref. [62] under a Creative Commons license CC BY 3.0; land cover image adapted from ref. [34] under a Creative Commons license CC BY 4.0; fraction of absorbed photosynthetically active radiation (FAPAR) image adapted from ref. [26], Copernicus Global Land Service (contains modified Copernicus Service information [2020]).

Some remote sensing biodiversity products do not scale to the original scoping of EBVs. This challenge is exaggerated by the original EBV formulations[4] that do not explicitly consider the inherent spatial, spectral, radiometric and temporal scales that are possible using remote sensing from space. Pixels do not represent an individual (object), such as a tree, and an individual (object) does not represent a pixel. An EBV[3] may be generated by fusing multiple remote sensing sources and in situ data. For instance, using the EBV class species traits, measuring the trait of a single organism of known species such as the height of a single oak tree[43] would require merging of very-high-resolution satellite imagery such as Planet Labs PlanetScope or DigitalGlobe WorldView imagery (to identify the tree), hyperspectral imagery such as DESIS or PRISMA (to recognize the species of the tree though unmixing) and LiDAR or stereoscopic pairs of very-high-resolution imagery (to measure the height of the tree).

Moving from the mapping of a species trait of an individual to mapping an EBV class at a landscape level (that is, ecosystem function and ecosystem structure) requires synoptic remote sensing imagery that covers an extent larger than an individual (object) at a grain size (resolution) appropriate to the EBV of interest. If a forest is a monospecific plantation[44] or dominated by a single species[45], the biological concept of species trait (such as the height of an individual tree of known species) merges with the remote sensing concept of the height of a forest stand or habitat type (that is, the height of a group of trees of the same species)[43]. However, when an ecosystem contains multiple trees of different species, the information content of the data has to be interpreted in terms of a different biological concept (namely, community composition[46] rather than species trait).

Depending on the pixel resolution of the imagery, some biodiversity products such as LAI, vegetation height, net and gross primary productivity and green-up become relevant to multiple EBV classes (that is, ecosystem structure, ecosystem function, community composition and species traits). LAI occurs in three EBV classes (namely, species traits[47], ecosystem structure[48] and ecosystem function[49]). Net and gross primary productivity occur in two EBV classes (specifically, species traits[50,51] and ecosystem function[52]). A further example of a remote sensing biodiversity product not scoping to a single EBV class is phenology—the start, end and maximum of a season[53]—which typically incorporates various stages of greening across a range of scales from local to global (Table 2), with the pixel spatial resolution typically ranging between 2 m and 1 km. Phenology was originally conceived as an EBV candidate relating to the EBV class species traits and was directly attributed to an individual of a species[3,4,43]. However, land surface phenology is a concept relevant to the EBV class ecosystem function[24,54] (see Table 2). In addition, the remote sensing biodiversity products specific leaf area and foliar content of nitrogen, phosphorus and potassium occur in species traits[51,55] and ecosystem function[56,57], respectively. Based on these multiple EBVs that can benefit from remote sensing biodiversity products, it is important to consider harmonization of the in situ measurements needed globally to calibrate and validate across these products.

EBVs are essentially biological. EBVs are essentially biological, although abiotic disturbances of ecosystems are intimately linked to the diversity of life. Ecosystem disturbance remains a candidate EBV[3], even if this has been challenged[58] on the grounds that inundation, fire and other disturbances do not constitute EBVs as they are not biological. However, ecosystem disturbance is a commonly used term in remote sensing[59] for measuring the impact of a non-periodic disturbance on an ecosystem (Supplementary Table 1). For example, a forest fire can only occur in the presence of biomass, so it is linked intimately to the biology of life and can be readily discriminated by remote sensing[60–62]. Consequently, in Supplementary Table 1, we recognize the biological impact of irregular disturbances (for example, biological effects of fire disturbance) as remote sensing biodiversity products. We exclude as remote sensing biodiversity products those ancillary abiotic variables such as elevation or tidal inundation, which have a periodic biological cause and effect. Also excluded are human (land use) activities that impact biodiversity, since retrieving land use from space-borne remote sensing remains challenging as it requires local knowledge[63], although some human activities, such as identifying airports or discriminating residential from industrial areas, are increasingly inferred by machine learning[64]. Remote sensing may monitor a

Table 2 | The 30 remote sensing biodiversity products with the highest rankings

Number	Remote sensing biodiversity product	Remote sensing-enabled biodiversity variable	EBV class	Rank within EBV class	Rank across all EBV classes
1	Biological effects of fire disturbance (direction, duration, abruptness, magnitude, extent and frequency)	Ecosystem disturbance	Ecosystem function	1	1
		Habitat structure	Ecosystem structure	1	1
2	Biological effects of irregular inundation	Ecosystem disturbance	Ecosystem function	1	1
		Habitat structure	Ecosystem structure	1	1
3	LAI	Ecosystem physiology	Ecosystem function	3	5
		Habitat structure	Ecosystem structure	3	5
		Species physiology	Species traits	1	21
4	Land cover (vegetation type)	Habitat structure	Ecosystem structure	3	5
5	Ice cover habitat	Habitat structure	Ecosystem structure	5	8
6	Above-ground biomass	Habitat structure	Ecosystem structure	6	9
7	Foliar N/P/K content	Ecosystem physiology	Ecosystem function	4	9
		Species physiology	Species traits	2	28
8	Net primary productivity	Ecosystem physiology	Ecosystem function	5	11
		Species physiology	Species traits	2	28
9	Gross primary productivity	Ecosystem physiology	Ecosystem function	5	11
		Species physiology	Species traits	2	28
10	Fraction of absorbed photosynthetically active radiation	Ecosystem physiology	Ecosystem function	5	11
11	Ecosystem fragmentation	Spatial configuration	Ecosystem structure	7	11
12	Ecosystem structural variance	Spatial configuration	Ecosystem structure	7	11
13	Urban habitat	Habitat structure	Ecosystem structure	7	11
14	Vegetation height	Habitat structure	Ecosystem structure	7	11
15	Plant area index profile (canopy cover)	Habitat structure	Ecosystem structure	7	11
16	Habitat structure	Habitat structure	Ecosystem structure	7	11
17	Fraction of vegetation cover	Habitat structure	Ecosystem structure	7	11
18	Specific leaf area	Ecosystem physiology	Ecosystem function	8	22
		Species morphology	Species traits	2	28
19	Chlorophyll content and flux	Ecosystem physiology	Ecosystem function	8	22
		Species physiology	Species traits	2	28
20	Land surface peak (maximum of season)	Ecosystem phenology	Ecosystem function	8	22
	Land surface green-up (start of season)	Ecosystem phenology	Ecosystem function	8	22
	Land surface senescence (end of season)	Ecosystem phenology	Ecosystem function	8	22
21	Carbon cycle (above-ground biomass)	Ecosystem physiology	Ecosystem function	8	22
22	Peak season (maximum of season)	Species phenology	Species traits	2	28
23	Green-up (start of season)	Species phenology	Species traits	2	28
24	Senescence (end of season)	Species phenology	Species traits	2	28
25	Leaf dry matter content	Species morphology	Species traits	2	28
26	Ecosystem soil moisture	Ecosystem physiology	Ecosystem function	14	28
27	Functional diversity	Community diversity	Community composition	1	38
28	Species abundance	Population abundance	Species population	1	46
29	Relative species abundance	Population abundance	Species population	1	46
30	Population density	Population structure by age/size class	Species population	1	46

change in state, such as decreased forest green biomass, but the cause of the reduced green biomass—whether it is selective logging or storm damage—cannot be detected globally by remote sensing[36] and consequently is not included in Supplementary Table 1. With the wider use of artificial intelligence (for example, expert and knowledge-based systems)[31,65] and deep learning (for example, artificial neural networks, decision trees and random forests)[66–68], land cover mapping is becoming easier and more accurate (for example, in discriminating forest types).

Some original EBVs can be merged into a single remote sensing-enabled biodiversity variable. The original EBV candidates live cover fraction and ecosystem vertical profile are both remotely sensed measures of vegetation cover, as well as 3D structure[69]. However, in remote sensing, habitat structure is a widely used term[70,71] that can include land cover, vegetation height, LAI, deadwood, ocean fronts and so on. In Supplementary Table 1, we concatenate these remote sensing products (the EBV candidates live cover fraction and ecosystem vertical profile) into the single remote sensing-enabled biodiversity variable habitat structure. This 3D variable is differentiated from the often-termed spatial configuration[72,73], which refers to the 2D spatial pattern of land cover fragmentation and its variation. Some original EBV candidates can also be directly informed by a single remote sensing-enabled biodiversity variable. Examples include ecosystem phenology, primary productivity, ecosystem disturbance and species distribution (Supplementary Table 1).

Retrieving products from remote sensing that are useful in the construction of EBVs demands that the remote sensing community parsimoniously merges and simplifies its terminology. For a candidate EBV such as phenology, it is possible to calculate a series of related remote sensing products (for example, start-of-season, peak season and end-of-season products[54,74]). The solution to avoiding lengthy lists of candidate EBVs (Supplementary Table 1) is to merge similar remote sensing biodiversity products into a single EBV, especially when the products have comparable feasibility for implementation by remote sensing.

We adopt the newly proposed EBVs for species traits (refs. [3,75] and N. Fernandez, in review). Many biodiversity products generated by aircraft- or unmanned aerial vehicle-borne sensors (for example, vascular plant traits[76–81]) are not yet mature for routine global production. However, such datasets are still valuable, providing support for in situ measurements when validating the ecological accuracy of satellite-based data. Although there are currently no global biodiversity products available that allow direct measurement and monitoring of species-level trait changes across time (that is, for an individual organism)[75], we are optimistic that improvements in space-borne high-resolution hyperspectral satellites[10,82,83], along with the next-generation space-borne LiDAR[84], will bring us closer to generating a full suite of EBV classes at a global level, including species traits from space[85,86].

Some EBVs are not directly measurable by remote sensing from space. Although some widely cited forum and perspective papers have speculated that genetics and movement may be retrieved from remote sensing[87,88], the EBV class genetic composition[3,4] cannot yet be remotely sensed from space and is not considered further (Supplementary Table 1). Tantalizingly, recent research hints that remote sensing will make the EBV taxonomic/phylogenetic diversity (that is, a candidate EBV in the class community composition) retrievable for broad plant groups (orders and families) and foliar biochemical traits identified from reflectance spectra[89,90]. Time series of space-borne imagery also cannot retrieve movement, such as distance of dispersal or migration. It is only feasible to track movement using attachable global positioning system devices, which record an organism's position over time[91]. Although continuous video imaging has been demonstrated as a method to track vehicles from space, to our knowledge, this has not been applied to spatial ecology (large individual marine and terrestrial mammals have been detected under specific environmental conditions but not tracked by satellite remote sensing[20,92,93]). However, linking animal movement with remotely sensed environmental data provides ecologically relevant information on species–environment interactions[94].

Prioritizing biodiversity products retrievable from satellite remote sensing

The remote sensing biodiversity products (Supplementary Table 1) formed the basis for the prioritization of biodiversity products from satellite remote sensing. Ranking these remote sensing products has practical consequences for prioritizing the measurement of biodiversity from satellites. For example, products in the EBV class species traits[3] scored the lowest possible score of 3 for maturity (see Supplementary Table 2; the ranking is explained in Table 1), indicating that it should not be a priority because the retrieval of species traits from satellite remote sensing is still immature and unfeasible at this time. Nonetheless, we retain species traits in the 30 highest-ranking remote sensing biodiversity products (see Table 2, which summarizes the 30 remote sensing biodiversity products with the highest rankings from Supplementary Table 2), as this EBV class will probably be retrievable from space within the coming decade thanks to the fusion of imagery from planned space assets (that is, from satellites providing higher spatial, spectral, temporal and radiometric resolutions). For all remote sensing biodiversity products (Supplementary Table 3), we cite a relevant reference and indicate which SDG and CBD Aichi target each product informs. We also estimate the remote sensing data specifications necessary to capture the relevant biodiversity product (Supplementary Table 4). Note that Supplementary Table 4 is a preliminary estimate that will be subject to further refinement and revision as part of the science traceability approach[95] adopted by NASA and the European Space Agency[96,97].

Reporting using remote sensing-enabled biodiversity variables

We have compiled a comprehensive, prioritized list of which remote sensing biodiversity products can contribute information to the list of EBVs[3], based on their relevance, feasibility, accuracy and maturity. By translating between the candidate EBVs[3] and remote sensing-enabled biodiversity variables (Supplementary Table 1), as well as providing a corresponding list of remote sensing biodiversity products recognized in both remote sensing and the biological sciences, we propose a novel approach to coordinate and communicate between networks of observers, especially between space agencies (as the data providers) and well-established communities providing the in situ data (for example, eLTER, LifeWatch, GEO, GEO BON, ForestGEO, GBIF, NEON, ILTER and Fluxnet). The importance of harmonized, easily accessible, analysis-ready remote sensing biodiversity products is recognized not only by those who generate biodiversity products, but also by policymakers and scientists, as detailed in Supplementary Table 3.

This analysis focuses on biodiversity products that can be retrieved from space using current or planned space assets. The operational high-resolution remote sensing biodiversity products providing ecosystem-level information[98] were highly ranked, as detailed in Table 2 and Supplementary Table 4. Specifically, remote sensing products describing abiotic drivers of biological disturbance, including biological effects of irregular inundation[37] and biological effects of fire disturbance[60,99] (Table 2 and Supplementary Table 2) were ranked the most highly in terms of relevance, feasibility, accuracy and maturity. Interestingly, these most mature and accurate biodiversity products are climate-related abiotic drivers of biodiversity. Another mature product strongly related to climate is land cover (for example, vegetation type, urban habitat and ice cover habitat). Such products have benefitted from large investments over the past 15 years in generating operational climate variables at a global scale from Earth observation[100]. In contrast, some remote sensing biodiversity products, though highly relevant and feasible, require further investment in satellite remote sensing for implementation at a global level. For example, as higher-spatial-resolution image spectroscopy and LiDAR satellites become available in the next decade, remote sensing products such as vegetation height and habitat structure, as well as remote sensing products for the EBV classes species traits, community composition and species populations, will probably be retrievable.

Other biodiversity products describing the EBV live cover fraction (for example, the land cover and LAI products; Table 2) were also highly ranked but scored lower than ecosystem disturbance due to their lower accuracy when implemented with satellite remote sensing. However, we note that specific land cover types, such as forest cover[101], are mature products, although their feasibility over the entire globe depends on operator interventions to tune output from the semi-automatic image classification algorithms used to process the satellite imagery.

The importance of harmonized, easily accessible, analysis-ready remote sensing biodiversity products is also recognized on national levels[102]. A number of remote sensing biodiversity products occurring in multiple EBV classes (as highlighted in Table 2 and Supplementary Tables 2 and 4) could be further prioritized by space agencies and other organizations for operational production at multiple resolutions and at a global scale, to support the CBD Aichi targets, SDGs and IPBES assessments (Supplementary Table 3). Yet, for remote sensing-enabled biodiversity variables to contribute to monitoring progress towards meeting policy goals, including the CBD biodiversity targets, SDGs, IPBES assessments and National Biodiversity Strategies and Action Plans, remote sensing biodiversity products need to be available at policy-relevant time frames. Supplementary Table 3 summarized the potential of the remote sensing biodiversity products to support the CBD biodiversity targets and SDGs[7,11,12]. In general, policy-level time frames require changes in biodiversity to be detectable over decades, rather than periodic measurements (annually or seasonally)[103] that may be more suited to operational and research-orientated management and reporting.

More frequent detection of hotspots of change in biodiversity may be necessary, depending on the scale and extent of biodiversity change and the purpose for which the information is used[78,104–111]. The correct biological interpretation and attribution (training of models) for reporting the state and change in biodiversity relies on careful ground measurements using direct observation, but also ground cameras, sound recorders, mobile phones, electronic tags and fragments of genetic material sampled directly from the environment (eDNA)[112]. The importance of highly skilled specialists in biology cannot be overemphasized for the correct interpretation (validation) of remotely sensed products, especially when these products are extrapolated in space and used for forecasting the future[113].

As space agencies increase the number of Earth-observing space assets, and the number of Earth-observing satellites grows exponentially, interest is shifting to how engineers can design and build satellites that specifically address the needs of the biodiversity user community[114]. Despite policy settings, environmental regulation, laws and voluntary regulatory standards, biodiversity monitoring using in situ as well as remote sensing data remains underfunded[115,116]. Continuity of free and open data[117], affordability and access to ground research linked to remote sensing remain the keystones for globally monitoring biodiversity[117–119]. Further improvement of satellites for monitoring global biodiversity requires complex engineering trade-offs and dependencies between satellite observation parameters (for example, between spectral resolution and radiometric performance). The requirements demand close communication and an intimate understanding of both ecology and the potential and limitations of emerging satellite technologies by biologists and engineers. Remote sensing experts can and need to bridge between ecologists and space engineers by defining and translating terms, but also providing feasibility analyses (known as science and applications traceability matrices[95–97]) of specific satellite observation parameters and validating the resulting accuracy of remote sensing biodiversity products using in situ observations. This is a precondition to being able to consider technical trade-offs and ecological demands.

Outlook

Because many elements of biodiversity remain unseen or unknown when measuring global biodiversity change[69], here, we prioritize feasible and relevant biodiversity products that could be generated from satellite remote sensing with high accuracy, thereby filling data gaps in the spatial and temporal coverage of in situ biodiversity observations[120].

Recent developments for combining fragments of biological material (eDNA) with remote sensing show phylogenetic lineages, while genetic diversity can complement direct species observation when targeting conservation priorities[89,121–123]. All biodiversity-relevant remote sensing products will further evolve as remote sensing technology, as well as biological knowledge, develops. Future instruments planned for approximating a sufficiently high retrieval accuracy at the size of an individual species (for example, large trees) will allow a more complete description of all relevant EBVs[124]. Biodiversity metrics from space will become a reality once biological and engineering requirements are linked to end users of biodiversity-relevant remote sensing products.

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Author contributions
A.K.S. contributed to conceptualization, supervision, validation, visualization and analysis, as well as writing of the original draft preparation, review and editing. E.N. and A.A. contributed to conceptualization, investigation, analysis, writing, reviewing and editing. N.C.C., M.E.S., W.D.K. and R.D. contributed to conceptualization, visualization and analysis, as well as writing, reviewing and editing. M.P., P.V., H.F., M.F., N.F., N.G., I.G., U.H., M.H., D.H., S.H., F.E.M.-K., R.V.D.K., A.L., P.J.L., M.C.L., C.A.M., B.O., D.R., W.T., J.K.V., T.W., M.W. and V.W. contributed to conceptualization, analysis and reviewing the draft.

Competing interests

The authors declare no competing interests.

Additional information

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