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REVIEW

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Advancing optical earth observation for EU policies: needs, opportunities, recommendations

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Abstract

The effective translation of Earth observation (EO) measurements into actionable information for agriculture and land monitoring is critical to support policy implementation on climate, environment, and sustainable development. However, this translation remains challenging, as EO evolves from an awareness-raising instrument into an operational tool for evidence-based policymaking. To address this gap, we systematically link, for the first time, European Union (EU) land-related agricultural and environmental policies to EO-derived variables that can be generated from enhanced optical satellites expected in the next decade. We present a comprehensive framework for assessing the technology readiness levels (TRLs) of EO variables used to map, monitor, and manage crop, forest, soil, mineral, and water resources, thereby facilitating policy implementation and compliance. Upcoming Copernicus Hyperspectral Imaging Mission for the Environment (CHIME), and the Sentinel-2 Next Generation (S2NG) missions, both developed by the European Space Agency (ESA), will deliver substantial technological advancements for high-level EO-based products, enabling applications such as plant nitrogen and soil organic carbon content (SOC) estimation, species identification, and water quality characterization. Realizing the full potential of CHIME and S2NG for agricultural and environmental policy implementation will require advancing current products from prototype stages (TRL 4–6) to full operational readiness (TRL 9) through robust science-policy interfaces. Within such interfaces, we recommend exploiting existing (hyperspectral) EO data and time series, strengthening in-situ observations for robust model development and validation, and testing synergies between systems. Co-design of tailored products with policymakers is then essential to refine algorithms and align EO outputs with regulatory needs and scales. Upcoming spaceborne imaging spectroscopy and enhanced multispectral data streams thus have the potential to become game-changers and indispensable tools for EU policy implementation, providing greater traceability of key environmental and agricultural processes.

Keywords CHIME, EU legislation, Copernicus, Expansion missions, Sentinel-2 next Generation, User involvement, EO variables

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Introduction

Mitigating and adapting to global change requires sustained long-term monitoring of the Earth system, as prioritized by the Millennium Ecosystem Assessment [140, 148]. In support of this, Earth observation (EO) has achieved remarkable advances in recent years, driven by technological innovations with numerous new sensors [162] and increased global awareness of environmental challenges, such as urban expansion, deforestation, forest degradation, or agricultural intensification, among others (e.g., [101, 122, 168]). Since the introduction of the European Green Deal (EGD) [33] in December 2019, the European Commission (EC) has proposed and revised several land-related environmental and agricultural policies, which have subsequently been adopted by the European Union (EU). The new regulatory framework focuses on the protection and restoration of natural resources, aiming to combat climate change, enhance biodiversity, promote sustainable land use, and increase ecosystem resilience, thereby contributing to the EGD's objective of achieving climate neutrality by 2050 [136, 163]. Value-added products derived from EO data can greatly support this agenda by providing consistent, repeatable monitoring across Member States in support of implementation, reporting and compliance.

However, the practical uptake of EO products for policy monitoring and compliance remains challenging, partly because relevant institutions and implementing agencies often have limited awareness or technical capacity (e.g., [11, 21]). The Copernicus Programme, established under Regulation (EU) 2021/696 (EU, 2021c) and funded by the EU, provides a comprehensive suite of products and services, with the European Space Agency (ESA) leading the development and operation of the Sentinel satellite series. Hereby, the Copernicus Land Monitoring Service (CLMS)[1] delivers user-ready information products across various domains. The current product portfolio primarily relies on data from radar and multispectral Sentinel satellites, such as Sentinel-1, Sentinel-2, and Sentinel-3, providing broad support for environmental and land policy implementation. Sentinel-2, the most widely used Copernicus sensor for land monitoring, features spatial resolutions of 10–20 m (and 60 m atmospheric/cirrus bands); 13 spectral bands spanning visible to shortwave-infrared (SWIR) (i.e., 443–2190 nm); and a 5-day temporal revisit at the equator, enabling precise crop, soil, and vegetation analysis central to EU agricultural and environmental policies (Drusch et al., 2012)63. While CLMS and other services already provide operational products, there is ample room for improvement [11], for instance, in the domain of inland water quality [113].

Towards the end of this decade, the Copernicus Hyperspectral Imaging Mission for the Environment (CHIME) [24, 145] is anticipated to routinely deliver data with high spectral resolution (~250 bands), 30 m spatial resolution and a repeat cycle of 11 days, complementing the data streams currently offered by multispectral systems like Sentinel-2. Furthermore, the Sentinel-2 Next Generation (S2NG) mission with the Advanced Multi-Spectral Instrument (AMSI), planned for launch in the early 2030s, will offer enhanced multispectral capabilities by providing additional spectral bands for specific applications, a higher repeat cycle of 2–3 days, and finer spatial resolution than Sentinel-2 and CHIME (i.e. 5–10 m). In addition, the Land Surface Temperature Monitoring (LSTM) mission is planned for launch in 2028 as part of the Copernicus Sentinel family. The satellite will carry instruments capable of observing in the thermal infrared (TIR), SWIR, and visible to near-infrared (VNIR) spectral ranges in 50 m spatial resolution within 1–3 days, providing data over land and coastal areas to support agricultural management and potentially a broad range of other environmental services. CHIME-derived data will offer key advantages. Building on the experience from the new generation of spaceborne imaging spectroscopy precursor missions, i.e. PRecursore IperSpettrale della Missione Applicativa (PRISMA) [119] and the Environmental Mapping and Analysis Program (EnMAP) [27], CHIME is expected to further enhance the accuracy of mature, high technology readiness levels (TRL) products such as leaf area index (LAI) and water-quality variables (e.g. [117], Niroumand-Jadidi et al., 2020133; [165]). In addition to accuracy improvements, the temporal and spatial resolutions of these mature products will be further enhanced mainly through S2NG. In particular, the higher spectral dimensionality of the new sensors will enable the retrieval of currently unreliable or unattainable biophysical and biochemical variables from traditional multispectral data. Such capabilities open new possibilities for quantifying crop and soil properties, water and nutrient status, species discrimination, and biodiversity or ecosystem traits (e.g., [89, 93, 109, 128, 164, 166, 170, 173]). This will directly support EU policies like the Common Agricultural Policy (CAP) for crop monitoring and eligibility checks, the EU Land Use, Land Use Change and Forestry (LULUCF) for emissions/land-use verification, or the Regulation on deforestation-free products (EUDR) for deforestation-free supply chains, where finer spectral/temporal resolutions enable near-real-time compliance and food security assessments facing climate challenges.

In summary, numerous scientific studies provide evidence of the added value of data with enhanced spectral,

[1] https://land.copernicus.eu/en

spatial and temporal detail, compared to currently available sensor data. In the coming years, it will be crucial to improve scientific algorithms and enhance the accuracy of derived variables to develop mature products that support policymakers, land managers, and authorities responsible for monitoring and compliance tasks [153]. To achieve this, a program that explores and demonstrates the potential of EO data to address pressing policy needs is required (Fig. 1).

Accordingly, this study aims to guide the development of value-added EO products by identifying key variables whose retrieval can be enhanced through improved sensor technologies. Thus, by carefully examining EU land-related policies and evaluating the capabilities of emerging sensor technologies, we aim to:

- assess the maturity of EO-derived key variables for mapping, monitoring, assessing, and managing environmental ecosystem services and
- provide guidance on how to bridge the gap between the current status and full maturity, enabling routine production and operational provisioning to support policy implementation and compliance.

Note that in this study, we focus primarily on advances in optical imaging spectroscopy and high-resolution multispectral missions (CHIME and Sentinel-2 NG) as key enablers for EU policy monitoring based on their capability to provide specific variables. Thermal missions such as LSTM offer important but partly distinct capabilities, particularly for evapotranspiration, crop water use, and land surface energy balance quantification.

Review of selected EU land-related policies and linking to relevant EO-derived variables

For categorisation of policies, we aim to align with the EU policy areas defined by the Knowledge Centre on Earth Observation (KCEO) (see KCEO [102]). We acknowledge that there are alternative classifications and that none fully capture the practical overlaps, synergies, and mutual influences among policies, many of which reinforce and affect one another. The following policy areas are covered in our analysis: Agriculture, Forestry, Climate Change Mitigation and Climate Change Adaptation (jointly: Climate), Biodiversity, Soils, Raw Materials, as well as Inland Water and Pollution, and Coastal Zones Management (jointly: Water).

Agricultural policies

EO data have become indispensable for policy stakeholders under the CAP and are increasingly central to its monitoring systems. Simplification measures introduced in May 2025 [47] promote greater reliance on satellite-based and digital tools to reduce physical inspections, further increasing demand for EO-derived information. Sentinel-2 has long been the cornerstone for agricultural monitoring, underpinning the digital transition toward Agriculture 4.0 and initiatives such as the European Farm to Fork strategy [35]. Its products, from cropland and crop type maps to biophysical and phenological

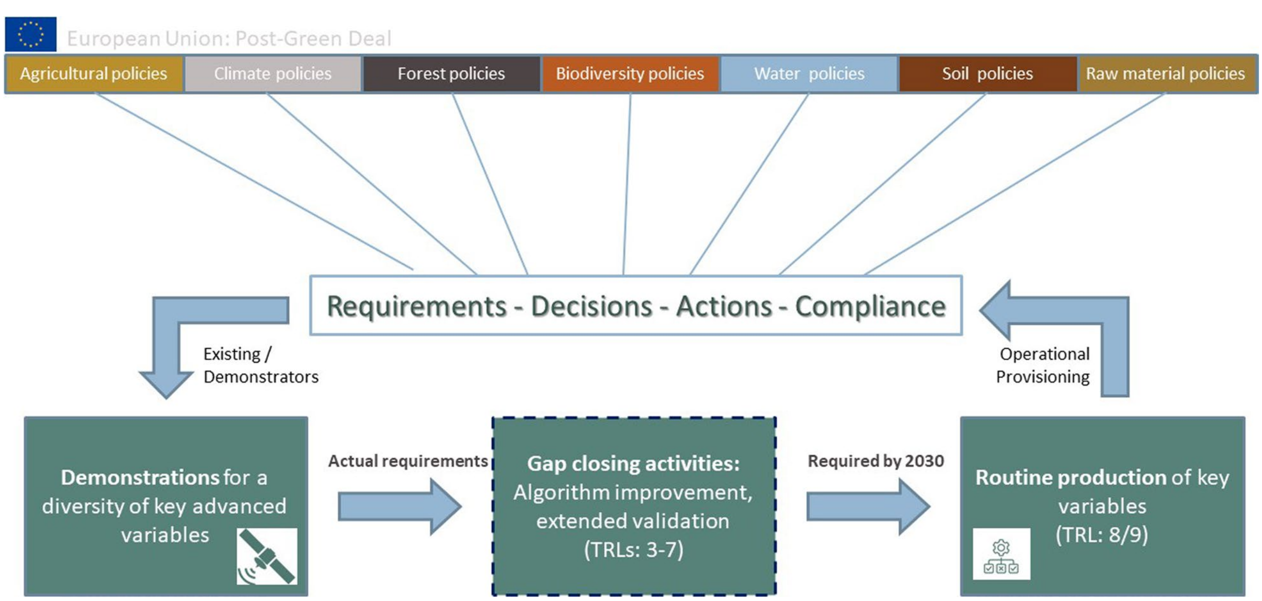

Fig. 1 Requirements, decisions, actions, and compliance for EU policies supported by EO-derived key variables. From enhanced spectral information to demonstrations and routine production. Rationale of the current study. TRL: technology readiness levels

indicators, support parcel-level management and more accurate crop statistics.

The CAP 2023–2027 period marked a shift toward results-oriented and sustainability-focused policies aligned with the European Green Deal (EGD) and the United Nations (UN) Sustainable Development Goals (SDGs). The framework's conditionality, reinforced through Good Agricultural and Environmental Conditions (GAEC) standards and eco-schemes, moves from compliance-based controls to outcome-based incentives addressing climate, soil, water, and biodiversity goals. This transition now relies on continuous satellite-based area monitoring using Sentinel-1 and Sentinel-2 time series rather than being limited to on-site inspections.

Looking ahead, the proposed CAP 2028–2034 [48] consolidates monitoring approaches, linking income support to verified environmental performance through the Degressive Area-Based Income Support (DABIS) and a new "farm stewardship" system. These, together with the agri-environmental and climate actions (AECAs), reward sustainable practices in crop and livestock systems. The next CAP will therefore depend even more on spatially explicit, frequently updated indicators to assess sustainability outcomes, land-use intensity, and environmental performance across Europe. Besides the provision of new added-value products, future EO sensors will be instrumental in maintaining and enhancing existing agricultural data provision and related services.

Forest policies

The 2019 Communication "Stepping Up EU Action to Protect and Restore Forests" (COM (2019) 352 final) Commission [32] represented a decisive step by the EU to phase out its role in global deforestation, establish partnerships, mobilize sustainable finance, and build robust information systems. On the home front, this was followed by the adoption of the EU Forest Strategy for 2030 (COM/2021/572) Commission [41] to improve the quantity and quality of EU forests, and strengthen their protection, restoration and resilience. As a horizontal support for these goals, the Strategy pays special attention to strategic forest monitoring, reporting and data collection. Traditional forest monitoring via national forest inventories collects a wealth of data at defined sites but requires significant financial investments and typically operates on re-measurement cycles of about 5–10 years only. In this context, EO-derived data products and frequently updated geospatial layers with EU or global coverage will play a pivotal role in supporting the implementation and monitoring of forest-related policies, for example, through wall-to-wall maps of tree cover, forest type and biomass change. However, some of the most crucial forest policies have faced significant political opposition, as illustrated by the proposed but ultimately rejected Regulation on a monitoring framework for resilient European forests (Forest Monitoring Law, COM(2023) 728 final, Commission [43]). In November 2025, the European Parliament backed a one-year postponement and simplification of the EUDR (Regulation (EU) 2023/1115, EU [75]), aligning with the Council's call to delay application deadlines and ease due diligence requirements, especially for micro and small operators. Since the core objective of the EUDR (deforestation-free supply chains) remains, the need for robust spatial evidence persists, and the demand for reliable, consistent EO data and derived land-cover/change products can be expected to grow.

Climate policies

The EU's overarching climate objective is set out in the European Climate Law (Regulation (EU) 2021/1119) [72], which establishes a binding target of climate neutrality by 2050 and at least a 55% reduction in net greenhouse gas emissions by 2030, compared to 1990 levels, together with a framework for climate adaptation and carbon removals. Building on this, the Council has now agreed to amend the law by introducing a binding intermediate 2040 target of a 90% reduction in net GHG emissions relative to 1990, alongside provisions on flexibility and key design elements that will guide post-2030 climate policy while still requiring deep decarbonisation across all sectors and an enhanced role for carbon sinks. The land use sector, encompassing cropland, grassland, wetlands, forests, and settlements, offers significant carbon sequestration and emission reduction opportunities. The EU LULUCF (Regulation (EU) 2023/839, Commission [45]) is a cornerstone in this fight against climate change. The LULUCF Regulation introduces the EU-wide GreenHouse Gas (GHG) net removals target and specific carbon budgets for all Member States for 2030, which should be tracked based on regularly reported emissions and removals, leveraging precise data obtained via advanced monitoring technologies, including EO-derived data and updated geospatial layers. At the end of 2024, the EC adopted the EU Carbon Removal Certification Framework (CRCF) (EU) 2024/3012) [77]. The CRCF differentiates between three primary categories of carbon removal: (i carbon farming, encompassing afforestation and reforestation, improved forest management, agroforestry and mixed farming, soil protection measures (conservation tillage, cover crops, catch crops, rewetting and restoring peatlands and wetlands, and efficient use of fertilisers, (ii permanent carbon storage,and (iii carbon storage in long-lasting products.

Biodiversity policies

The EU Biodiversity Strategy for 2030, COM/2020/380 final [37] sets ambitious goals to ensure that ecosystems are healthy, resilient to climate change, rich in biodiversity and able to deliver essential ecosystem services. It includes specific targets to protect a minimum of 30% and strictly protect a minimum of 10% of EU land area and integrate ecological corridors, and to restore degraded ecosystems. It also strengthens monitoring by extending national requirements of Member States, and developing new indicators [67]. The Nature Restoration Regulation (NRR, Regulation EU) 2024/1991) [76] was adopted in June 2024 as the key element of the Biodiversity Strategy, aiming to achieve a harmonized framework for monitoring and restoring degraded ecosystems. The regulation sets binding targets for the restoration of terrestrial, freshwater and urban ecosystems. By 2030, at least 30% of EU land and sea areas that are not in good condition should be under restoration, with the aim of restoring at least 90% of ecosystems by 2050. This includes the conservation status of Natura 2000 habitat types, which should be enhanced from unfavourable to favourable conditions, and prioritized for restoration until 2030. Restoring natural connectivity of rivers and the ecological functions of associated floodplains is also promoted, with the objective of returning at least 25,000 km of rivers to free-flowing conditions by 2030. Restoration of forest ecosystems should lead to an increase in standing and lying deadwood, unevenly-aged forests, forest connectivity, and abundance of organic carbon stocks. Within its objective of enhancing biodiversity in agricultural ecosystems, the NRR emphasizes protecting and restoring wetlands, particularly peatlands, as a cost-effective approach to mitigating climate change. Finally, the NRR aims to increase the trend of urban green space and of urban tree canopy as measures for restoring urban ecosystems.

EU Member States must develop national restoration plans by September 2026, outlining how they intend to meet restoration targets. Regular monitoring and reporting on progress is envisaged, leveraging, among others, data and services from EO technologies. While Copernicus products are central for the monitoring under the NRR, the implementation phase remains adaptable, allowing for the integration of advanced national products, such as high-resolution land-cover and habitat maps, tree species, or biodiversity indicators.

Soils policies

Estimating SOC using remote sensing is growing in importance for carbon cycle monitoring and agriculture, and is among the most requested variables across policies. A large proportion of EU soils (70%) is currently in unhealthy conditions and affected by widespread degradation [137]. In response, the Commission adopted the EU Soil Strategy for 2030 [39], aiming for a more comprehensive approach to ensuring soil and resilience, preventing land degradation by achieving no net land take and reducing soil pollution, and establishing common EU standards for the protection of soils, sustainable management practices, and restoration of degraded soils. In this framework, the EU Soil Observatory (EUSO) was established in December 2020 to track progress in soil management and restoration. A key component of the soil strategy is the Directive (EU) 2025/2360, the Soil Monitoring Law [78], which entered into force in December 2025. It addresses key soil threats in the EU, such as erosion, floods and landslides, loss of soil organic matter, salinisation, contamination, compaction, sealing, as well as loss of soil biodiversity. This law encourages Member States to utilize Copernicus services to monitor crucial soil descriptors (physical, chemical and biological variables) and assess overall soil health. Concurrently, the CAP has significantly emphasized agriculture's role in preserving soil fertility, and several of the GAEC elements specifically target soil conservation.

Raw materials policies

The Critical Raw Materials Resilience (COM/2020/474 final) [36] and the European Critical Raw Materials Act (CRMA, Regulation (EU) 2024/1252) [46] require improved mapping techniques for identifying a more diverse range of minerals. CRMA proposes a set of actions to ensure a secure and sustainable supply of raw materials while ensuring environmental safeguards and promoting circularity in their use. The key focus is to reduce dependence on a single third country (i.e., diversification of supply) while increasing transparency and sustainability in supply chains. Thus, the Act aims to identify Strategic Projects, improve recycling, and develop more sustainable sourcing methods within the EU. It explicitly acknowledges that EO data and derived services can support efforts towards sustainable critical raw materials value chains by providing a continuous flow of information for uses including exploration, environmental impact assessments, and mine monitoring, and encourages Member States to use EO data when designing their national exploration programmes, especially to survey remote or hard-to-access areas.

Water policies

The Water Framework Directive (WFD) 2000/60/EC [30] serves as the principal legislation for protecting and improving the quality of Europe's inland surface waters, transitional waters, coastal waters, and groundwater. It establishes the overarching objective of achieving "good ecological status" good ecological and chemical status for all water bodies by 2027, using River Basin Management Plan (RBMP) as the fundamental planning and implementation unit. The elements that make up ecological status include biological and chemical qualities, as well as hydromorphological characteristics of water bodies (e.g., riverbank structure and stability, river continuity). This overarching framework is reinforced by a set of thematic directives, such as the Bathing Water Directive (2006/7/EC), the Groundwater Directive (2006/118/EC), and the Environmental Quality Standards (EQS) Directive (2008/105/EC), which define priority substances and pollutants, along with the environmental quality standards that must be met to protect water bodies from degradation.

In 2022, a proposal to amend the WFD, the Groundwater Directive, and the Environmental Quality Standards Directive was initiated by the EC as part of the EGD's goal to protect and restore Europe's natural environment. The Bathing Water Directive focuses on microbial water quality, where EO may help identify contributing environmental conditions such as eutrophication or algal blooms. The Drinking Water Directive (EU) 2020/2184 establishes safeguards to protect human health from water contamination, ensuring that drinking water remains wholesome and clean, and aims to improve universal access to safe drinking water across the EU. To this end, it defines a set of microbiological, chemical and indicator parameters for risk assessment, including turbidity, total organic carbon and water colour, which are among the variables that can potentially be mapped with remote sensing.

Traceability matrix of policy goals and key variables

To effectively explore the potential of future EO data in the context of EU policies, it is essential to establish a clear and transparent link between specific policy objectives, outlined above, and the remotely sensed variables relevant for monitoring and assessing progress. Table 1 presents a traceability matrix, associating selected policies with their target areas and identifying key EO-based variables that can be estimated through advanced spectral, spatial, or temporal capabilities. It is important to note that while many of these variables have previously been derived from multispectral sensors (primarily Sentinel-2/Landsat), the absence of key spectral features or limited temporal frequency constrains the accuracy of such estimations, resulting in increased uncertainty (e.g., [27, 145, 164]).

The upcoming EO satellite missions: CHIME and S2NG

Hyperspectral imaging mission for the environment: CHIME

CHIME is part of the future Copernicus Sentinel Expansion missions[2] and it will provide routine and openly available hyperspectral observations (i.e., contiguous spectral bands from the visible to the SWIR) through the Copernicus Programme. The mission, to be comprised of two satellites (CHIME-A and CHIME-B), will carry a pushbroom grating imaging spectrometer with high signal-to-noise ratio (SNR), high radiometric accuracy and data uniformity [132]. The instrument consists of a single telescope for three single-channel spectrometers covering each one-third of the total swath of ≈130 km. Each spectrometer employs a detector with 250 contiguous narrow bands in the visible, near-infrared (NIR), and SWIR spectral regions (400–2500 nm) [20], see Fig. 2. CHIME will provide routine global coverage of land and coastal areas at 30 m spatial resolution. The spacecrafts will fly in a sun-synchronous orbit, with a repeat cycle of 22 days for a single satellite or 11 days for two, ensuring a sub-seasonal time series of nadir-looking observations.

The primary objective of the CHIME mission is to enhance and innovate services for precise natural resource management, underpinning relevant policies and decisions. A key focus will be"sustainable agriculture and food security," encompassing food nutrition and quality [138].

In view of the current hyperspectral satellite data availability, the CHIME satellite mission is highly anticipated for its ability to deliver routine data with improved spatial coverage and temporal resolution, which is a key requirement for various applications. The mission will generate Analysis Ready Data (ARD) [8], and will leverage the valuable knowledge gained from demonstrations with precursors like Hyperion, PRISMA, EnMAP and EMIT. The availability of highly resolved spectral signals allows for full exploitation and validation of radiative transfer models (RTMs), unlocking the development of new products, e.g., Rautiainen et al. [146].

Sentinel-2 next generation: S2NG

The S2NG mission will continue the high-quality, high spatial resolution data series provided by the first-generation Sentinel-2 mission, while enhancing the existing capabilities where possible. The primary objective of the mission will remain land surface remote sensing, but a stronger emphasis will be placed on the provision

[2] https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Copernicus_Sentinel_Expansion_missions

Table 1 Traceability matrix from EU policy (post-EGD only, but note that some policies became EGD policies even though they were adopted before) over user needs and target variables

Post-EGD EU land-related policies ***grouped according to KCEO policy areas*** **(References)**	**Selected key target areas**	**Exemplary key variables** ***that require enhanced resolutions***
Agriculture: -CAP 2023–2027 ((EU) 2021/2115 /COM(2023)707 final) [74],Commission, 2023c), and CAP eco-schemes: Misurec et al. [127] -Farm to Fork Strategy (COM(2020)381 final [35]) - CAP2028-2034 Proposal [48]	-Adopting practices that minimise the negative impact of agriculture on the environment and climate through conservation agriculture -Monitoring of plant traits to characterise plants and detect crop stresses/diseases, and reduce the use of pesticides	-Soil organic carbon content -Canopy/leaf nitrogen content -Leaf pigment content -Canopy/leaf water content -Nonphotosynthetic vegetation -Detailed crop species
Forestry: -New EU Forest Strategy for 2030 (COM/2021/572) [41] - EU Stepping Up EU Action to Protect and restore Forests (COM (2019) 352 final) [34] -Regulation on Deforestation-free Products (2023/1115) [75]	-Contribute to achieving EU's biodiversity objectives and greenhouse gas emission reduction targets through: -Forest inventories & monitoring and sustainable forest management (SFM) -Improving health and biodiversity of forests -Protecting primary and old-growth forests -Avoid deforestation and forest degradation driven by agricultural expansion	-Species composition -Forest naturalness classes -Leaf pigment content -Vegetation water content -Canopy nitrogen content
Climate: -EU strategy on adaptation to climate change (COM/2021/82) [40] - European Climate Law (2021/1119) [72] -Communication on Sustainable Carbon cycles (COM(2021)800) [38] - 2023 EU Regulation on Land, Land Use Change and Forestry (2023/839), [45] -Carbon Removals and Carbon Farming Regulation (EU) 2024/3012 [77]	-EU LULUCF estimation and reporting, -National GHG inventories -Monitoring of climate extremes and impacts -Carbon farming (afforestation / re-forestation), including agroforestry, reduced tillage, cover crops, and peatland restoration -Permanent carbon storage -National reporting transparency	-Soil organic carbon content -Land cover (detailed) including vegetation type -Nonphotosynthetic vegetation -Leaf mass per area - Land use and forest cover change
Biodiversity: -EU Biodiversity Strategy for 2030 (COM(2020) 380 final) [37] -Nature Restoration Law (EU) 2024/1991 [76]	-Reduce ecosystems' vulnerability and improve their resilience and adaptive capacity -Binding restoration targets for specific habitats and species covering 20% of the EU's land and sea areas by 2030, and all ecosystems in need of restoration by 2050	-Leaf pigment content -Soil organic carbon content -Other top soil properties - Vegetation nitrogen content
Soils: -EU Soil Strategy for 2030 (COM/2021/699) [39] -Soil Monitoring Law (EU) 2025/2360 [78]	-Achieve healthy soils by 2050 (long-term target) -Sustainable soil management & restoration -Increasing data and monitoring on soils	-Soil organic carbon content -Bulk density -Soil erosion rate - Concentration of heavy metals
Raw materials: -Critical Raw Materials Resilience (COM/2020/474 final) [36]	-Improved mapping capabilities -Potential for targeting critical raw materials	-Mineral abundances and compositions, e.g.: -Base metals, Rare Earth Elements
Water: -Directive amending: the Water Framework Directive [30], the Groundwater Directive and the Environmental Quality Standards Directive [42], -Bathing Water Directive (BWD) currently undergoing amendment process [31]	- Mapping of rivers and water bodies and monitoring of water quality -Data for innovative decision-support systems	-Phytoplankton pigments and species -Coloured fraction of dissolved organic carbon -Harmful algal blooms

We only consider remotely sensed variables with proven added value when using enhanced spectral and spatiotemporal data. Main sources for target areas and key variables: Rast et al. [145] and as indicated below. While not exhaustive, the selection includes the most critical active land-related agricultural and environmental policy files

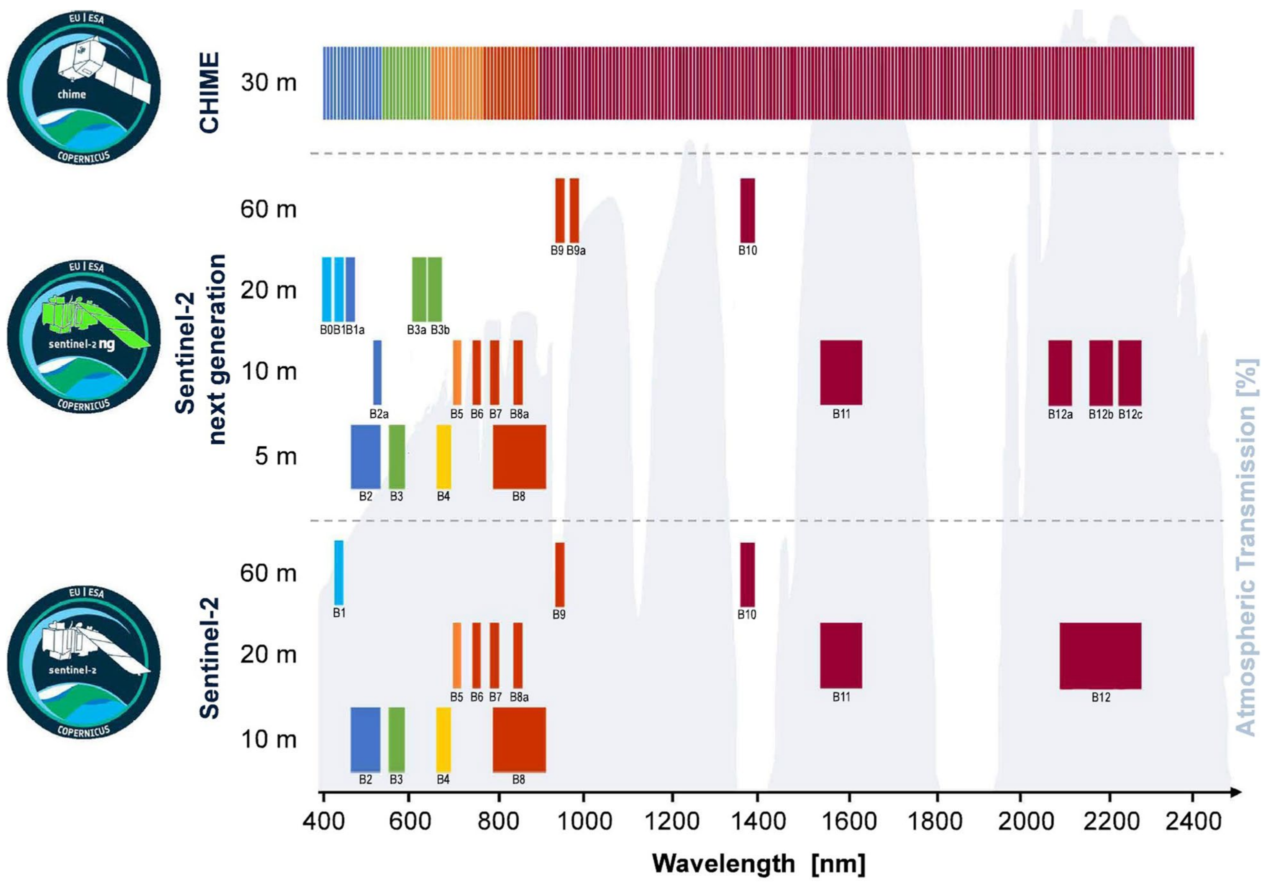

Fig. 2 Spectral and spatial configurations of Sentinel-2, S2NG and CHIME. Similarity of Sentinel-2 and S2NG bands reflects the key consideration of the mission on enhanced continuity, but also improved spectral information for new product provision. Continuous spectral coverage is represented by CHIME

of data for aquatic purposes, especially over coastal and inland waters, and on local to regional trace gas monitoring. S2NG aims to operate again as a tandem mission, with 21 spectral bands across the visible, NIR and SWIR wavelengths (Fig. 2). These bands will mostly be available at 5–10 m spatial resolution, and the mission will have a 5-day revisit time at the equator, improving to 2–3 days at mid-latitudes. Five new bands will be added in the visible wavelengths, one in the NIR and three in the SWIR, replacing the single SWIR band at ~ 2100 nm on first-generation Sentinel-2. Together, these new bands will provide opportunities beyond those offered by classical multispectral data.

The acquisition plan will be expanded for S2NG, providing full coverage of all marine Exclusive Economic Areas (EEAs) as well as a diverse set of additional targets requested by users of the first-generation Sentinel-2 mission. Meanwhile, advancements in sensor technology will enable a better SNR, allowing the separation of previously inseparable details, such as contrasts within shadowed areas or very dark surfaces like dense vegetation or water bodies.

A key concern for S2NG will be radiometric stability, both relative to the first-generation mission and between individual S2NG satellites. To reduce uncertainties in retrieved data products, the uncertainty budget for S2NG will be more rigorously quantified, enabling a more consistent propagation of measurement uncertainties through retrieval algorithms. Generally, the overall improvements in radiometric data quality will allow for improved data pre-processing outcomes and lead to higher quality data collection (e.g., [27]). Beyond improved resolutions, the steadily growing length of the data record will allow for in-depth change analyses that contribute to a better disentangling of long-term effects of climate change and land management impacts, among others. Additionally, the spectral alignment of S2NG with Landsat Next and the provision of a full set of legacy wavelengths between S2NG and Sentinel-2 (as well as Landsat Operational Land Imager) ensures long-term compatibility across sensor families.

Key variables obtained from enhanced spectral (spatiotemporal) information

Definition of technology readiness levels: TRL

In EO and applied remote sensing, developing vegetation, soil, and water products is a long and complex process. A standardized classification of maturity is therefore essential to understand current progress and the effort needed to achieve operational readiness. The Technology Readiness Level (TRL) framework provides such a benchmark, defining nine levels from basic research (TRL = 1) to fully operational deployment (TRL = 9) [70], see Table 2. Originally introduced for engineering and mission hardware by NASA and ESA, it is now widely applied to assess the maturity of EO-derived variables and Copernicus-related products.

For EO applications, TRL reflects combined readiness across three components: the underlying scientific basis, the technological capability of sensors and processing methods, and the extent to which the associated products have been demonstrated across different regions and environmental conditions. It thus indicates operational maturity rather than scale of implementation. Limiting factors affecting generalization (e.g., site-specific conditions or confounding variables) are discussed for each product. For example, hyperspectral crop disease detection may achieve high TRL only where no similar abiotic stresses interfere. Figure 3 presents the estimated TRLs for key variables analyzed in the following subsections.

Detailed vegetation species: forests and crops

Detailed knowledge of species in forests and agricultural land is vital for monitoring and management. Species identification using EO data is well-established: multispectral sensors such as Sentinel-2 and Landsat are widely used to classify crops and tree species at regional to continental scales. High-quality spectral information is crucial for distinguishing tree species, though the optimal acquisition time can be difficult to pinpoint [79, 99, 121]. The heterogeneity of European forests complicates mapping with coarser-resolution data, while Sentinel-2 has proven suitable for species differentiation [90, 95, 100, 155, 171], offering spatial, temporal, and spectral advantages over Landsat and even some commercial sources [56]. Existing large-scale products (e.g., Norway [19], Germany [15], Poland [91] mostly include dominant species, limited by reference data accessibility. The CLMS HRL Tree Cover and Forest datasets (10 m, 100 m,2017–2021 currently distinguish major forest types at pan-European scale. In view of thermal remote sensing data, the study by Richter et al. [149] demonstrated that tree species differ in canopy air temperatures by up to 4 °C, with remotely sensed land surface temperature data downscaled to 30 m resolution proving effective for modeling these species-specific cooling effects. Although agricultural areas appear more homogeneous, mapping still depends on spectrally pure pixels [65]. Sentinel-2's 10 m resolution provides higher accuracy than 30 m sensors [125]. Hyperspectral data at 30 m can distinguish similar crops when parcel sizes are compatible, but smallholder farming (< 2 ha, 12% of global agricultural land [142]) and agroforestry systems require higher resolution. Crop reference data are more accessible through sources such as LUCAS and national databases [5, 88], and the CLMS HRL Croplands layer provides 19 crop classes from 2017–2021.

We estimate the actual TRL at 6 for forest species mapping and 7 for crops, potentially reaching 9 once updated products support annual CAP reporting and global applications, including small-scale systems.

Leaf pigments: chlorophyll, carotenoids & anthocyanins

Leaf pigments such as chlorophylls, carotenoids, and anthocyanins are central to photosynthesis and photoprotection [52]. Chlorophyll drives photosynthesis and indicates plant stress [178], while carotenoids broaden the usable light spectrum and dissipate excess energy

Table 2 Definitions of technology readiness levels along with exemplary variables and references

Phase	TRL	Definition	Example of EO-derived variables
Invention	1	Basic principles observed	Phylogenetic diversity [21]
	2	Technology concept formulated	Leaf anthocyanin content [81]
Concept & validation	3	Experimental proof-of-concept	Leaf mass per area [82]
	4	Technological validity in the laboratory	Leaf protein content [80]
Prototyping	5	Technology validated in a relevant environment	Canopy nitrogen content [166]
Demonstration & pilot production	6	Technology demonstrated in a relevant environment	Soil organic carbon content [169]
	7	System prototype production in an operational environment	Grassland mowing practises [59]
Initial market introduction	8	The system is complete and qualified	SEN4CAP [16]
Market expansion	9	Actual system proven in operational environment	Products of the Copernicus Land Monitoring Service: e.g., LAI, fAPAR at 10 m daily

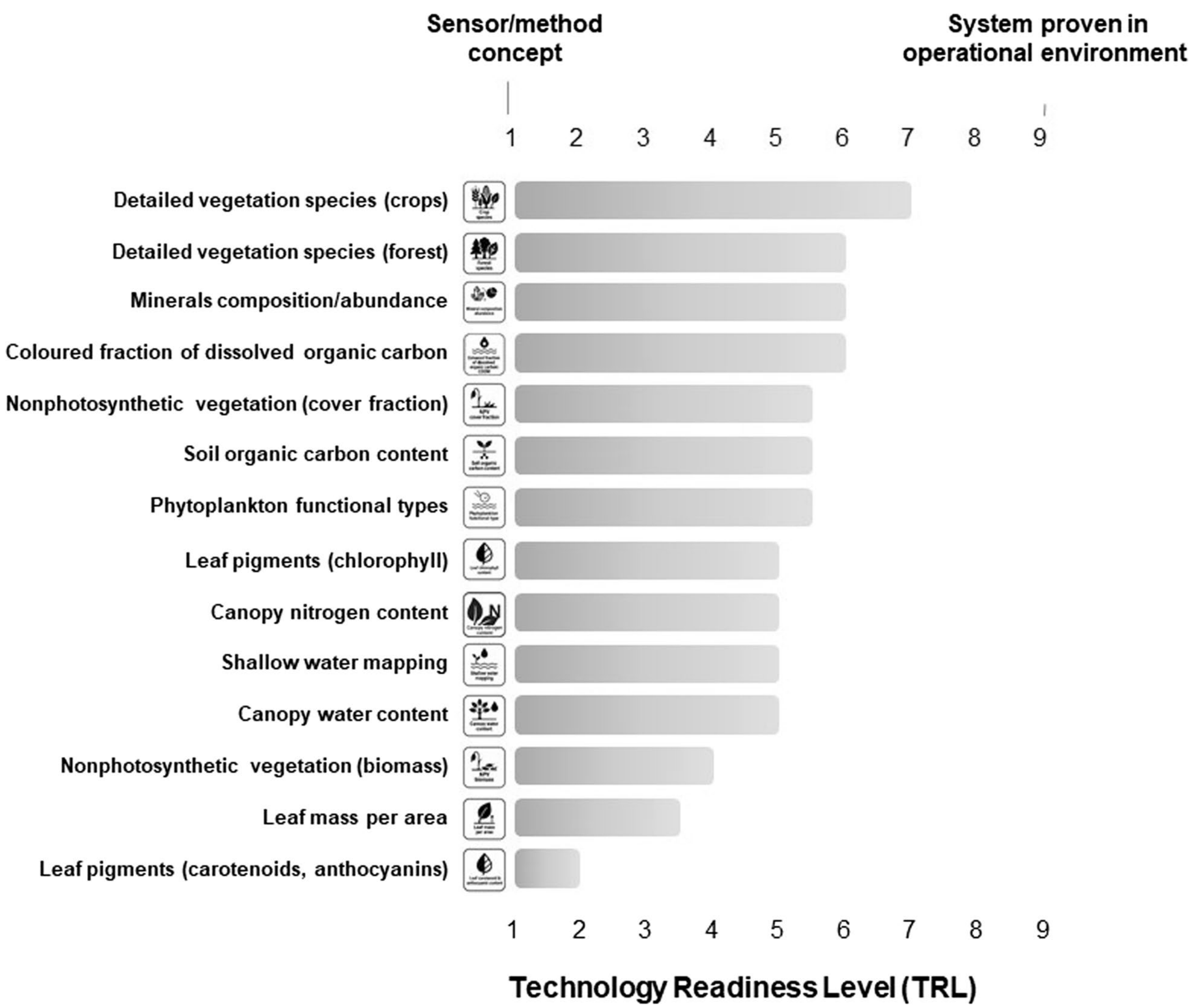

Fig. 3 Current estimates of TRLs for the analysed key variables, determined by the authors based on their expert judgement. These values are inherently uncertain and subjective, and should therefore be regarded as approximate ranges and as a starting point for more detailed, community-based assessments

(e.g., lutein, violaxanthin, zeaxanthin). Anthocyanins act mainly as photoprotective pigments, varying during the phenological cycle and giving leaves red to blue hues. In healthy vegetation, mid-season visible reflectance is dominated by chlorophyll. Remote sensing of chlorophyll has been explored since the 1970s [57, 143, 144, 160]. Multispectral approaches based on red absorption saturate at high chlorophyll levels, but narrowband sensors such as ENVISAT-MERIS and Sentinel-2 improved estimation by sampling the red-edge region (680–730 nm) [29]. The maximum slope of this region is highly sensitive to chlorophyll variation [55]. Despite mature retrieval methods, global chlorophyll products remain scarce,the first global map was produced from MERIS data (Croft et al., 2020b51. Carotenoids and anthocyanins receive less attention because chlorophyll dominates visible reflectance.

Overall, pigment effects on reflectance are well understood, yet progress is constrained by the limited availability of hyperspectral data, the need for better radiative transfer model parameterisation, and scarce ground data across species and seasons. Chlorophyll retrieval is relatively advanced (TRL = 5), while carotenoid and anthocyanin estimation remain less mature due to overlapping absorption features (TRL = 2).

Leaf mass per area: LMA

LMA is a key descriptor of plant strategies and photosynthetic capacity across vegetation types and climates. It quantifies leaf dry-mass investment per unit leaf area [174] (inverse of SLA) and is widely used to assess plant performance and ecosystem responses [147]. Within the leaf economic spectrum, LMA reflects trade-offs between resource acquisition and conservation: low-LMA species tend to have rapid growth and high photosynthetic and water transport rates [139], while higher LMA is associated with slower growth, more conservative resource use, and longer leaf lifespans, and is a strong predictor of growth rates, photosynthetic capacity, and litter decomposability [49]. LMA represents the cumulative effect of several biochemical constituents—mainly structural and non-structural carbohydrates and proteins, whose absorption features lie in the SWIR region [54, 83]. Its estimation from leaf spectroscopy is well established [82, 156]. Sentinel-2 imagery has been used for LMA retrieval [85, 94, 151], but sensitivity is limited by only two SWIR bands and high uncertainty. Data-driven approaches highlight additional predictors from visible to NIR bands [86], though generalisation across vegetation types remains challenging. Airborne imaging spectroscopy has demonstrated canopy-scale mapping potential, for example for quantifying forest canopy traits and diversity at metre-scale resolution [7, 28]. By contrast, spaceborne results from missions like EnMAP and PRISMA are still limited, as acquisitions cover fewer sites and shorter time periods, and methods for robust trait retrieval at 30 m resolution are only beginning to be tested at larger scales. Consequently, LMA estimation remains at a medium maturity level (TRL = 3–4), despite strong scientific understanding. Given its ecological relevance, ease of in-situ measurement, and the availability of robust physical and statistical models, LMA retrieval holds strong potential for rapid progress with moderate investment.

Canopy nitrogen content: CNC

Nitrogen (N) is a key macronutrient for plant growth and productivity. Adequate N availability supports yield and quality, while over-fertilization drives nitrate leaching, greenhouse gas emissions, and pest proliferation. Monitoring CNC is therefore central to smart farming and to assessing forest carbon sequestration, nutrient cycling, and health [118]. Leaf N typically ranges from 0.25–3.5% of dry mass, mostly within proteins and partly in chlorophyll [103]. Chlorophyll provides strong visible absorption, whereas protein features in the SWIR are weak and masked by water [154]. The chlorophyll–N relationship varies across species and time [14, 98], while protein–N relations are linear [80]. Hyperspectral sensing can detect N via chlorophyll and, to a lesser extent, proteins [84]. Protein-based estimations have advanced through PROSPECT-PRO [80] and its coupling with 4SAIL, enabling CNC retrieval by separating spectral signals of proteins and carbonaceous compounds [13, 141, 158, 166]. In highly fertilized crops, N saturation and limited in-field variability reduce the sensitivity of spectrally based algorithms, because CNC signals tend to saturate and become strongly correlated with biomass and LAI, making it difficult to distinguish additional N inputs. Nevertheless, recent studies demonstrate CNC mapping from multispectral Sentinel-2 data [17, 58]. Overall, CNC retrieval concepts from hyperspectral data are established (TRL = 3–4), based on laboratory and small-scale field studies [14, 80, 115]. Algorithm prototypes have reached TRL = 5, validated using PRISMA data in selected ecosystems [141, 158, 166].

Canopy water content: CWC

Vegetation water content provides key insights into plant physiological and ecological status, serving as an indicator of health and water availability. Water stress causes reduced transpiration and stomatal closure and affects nutrient and sugar transport [50]. Monitoring CWC supports applications in irrigation management, drought and yield assessment, ecosystem and carbon modeling [87], forestry [104], and fire risk evaluation [177]. At the leaf scale, water content can be expressed as relative leaf water content or Equivalent Water Thickness (EWT,$g cm^2$) [23]. At the canopy level, relevant indicators include live fuel moisture content (LFMC,%) [177] and CWC ($g\ cm^2$). Depending on the retrieval method, CWC may refer to green leaves only (product with Green Area Index, GAI [64]) or all living plant elements (product with Plant Area Index, PAI [120]). Optical CWC and LFMC retrieval [176] generally uses vegetation indices [114] or radiative transfer model inversion [71]. However, only one global product exists so far [120], with limited validation. In-situ measurements are challenging due to destructive sampling and strong vertical and horizontal variability [177].

Based on thermal data, Elsayed et al. [68] demonstrated that normalized relative canopy temperature derived from thermal imaging correlates strongly with canopy water content under arid and semi-arid conditions when integrated with hyperspectral VNIR/SWIR reflectance data.

We therefore estimate a TRL = 5 for CWC: methodological principles are established, but validation is constrained by measurement uncertainty and limited knowledge of spatio-temporal variability.

Non-photosynthetic vegetation: NPV

Non-photosynthetic vegetation (NPV) is a major component of plant biomass and a key variable for assessing ecosystem condition and functioning [164]. It remains one of the main uncertainties in quantifying above-ground carbon and is a critical factor in forest fire regimes. NPV includes crop residues, dry grasses, senescent leaves, and dead woody material [164]. Its principal constituents, lignin and cellulose, show distinct SWIR absorption features (2100–2300 nm) [69], providing the spectral basis for optical retrieval. Hyperspectral imagery is particularly well-suited for NPV quantification thanks to its ability to resolve these features [6, 27, 164]. Multispectral sensors also show sensitivity [106], though precision is limited by broad SWIR bands and soil background interference [130]. Upcoming missions with additional SWIR bands, such as S2NG and CHIME, aim to overcome these constraints [97]. NPV quantification approaches include estimating cover fraction or biomass per unit area [164]. The cover fraction method is most advanced due to its reliable retrieval by spectral unmixing [150] or regression models [106]. These have been applied across multiple scales and sensors, enabling local to global mapping and time-series analyses [9, 96, 134]. We estimate the current TRL for NPV cover fraction at 5–6, reflecting robust validation and growing integration into operational systems. NPV biomass retrieval remains at an earlier development stage (TRL = 4) [12].

Soil organic carbon content: SOC

Relevant spectral regions for estimating SOC are primarily located in the visible, NIR, and SWIR ranges. SOC content is strongly correlated with overall soil brightness and spectral reflectance, while diagnostic absorption features of other soil compounds decrease as SOC increases. The characteristic concave shape of the VNIR spectrum is particularly diagnostic of high SOC levels. For instance, bands around 530–570 nm, 600–780 nm, and 2200–2400 nm contain spectral signatures related to the stretching and bending vibrations of organic molecules (e.g., NH, CH, and CO groups). These wavelength regions highlight key spectral responses that make hyperspectral data well-suited for SOC prediction (e.g., [1, 10]). Recent studies further emphasize that combining visible, NIR, and SWIR bands enhances model performance, with SWIR wavelengths being particularly sensitive to SOC [1]. Moreover, beyond the optical domain (visible–NIR–SWIR), the TIR region has shown promising capabilities. Kopacková et al. (2017)105 demonstrated that the mid-infrared (3–12 μm) can provide quantitative information on organic soil samples and offers added value over the optical region.

SOC estimation from optical EO missions has recently been demonstrated in relevant environments using multispectral Sentinel-2 time series [170] and hyperspectral PRISMA satellite data [169], particularly in agricultural settings. Satellite time series from Sentinel-2 and Landsat enable accurate SOC mapping at local and field scales by targeting bare soil pixels across multiple dates, effectively minimizing vegetation/moisture interference through composites or phenological filtering. Multitemporal approaches substantially outperform single-date imagery, with pre-spring and fall optimal for bare soil detection and phenological parameters/diverse indices enhancing predictions [2], He et al., 2021; [66]. Recent advances include, among others, the multitemporal soil line methodology with neural network filtering to detect bare soil pixels across decades for accurate soil organic matter mapping at 30 m resolution [152]. More prominently, EO optical missions were largely used for SOC mapping and monitoring at the regional to large-scale.

Several large-scale models and algorithms have been developed and tested, for example, using Landsat or Sentinel-2 at continental to global scales [61, 170], often supported by continental soil databases that are already operational to some extent. Nevertheless, high uncertainties remain. Current research increasingly focuses on combining global soil data with AI-based soil spectral modeling using Sentinel-2 data to improve large-area SOC mapping accuracy [161]. At local and regional scales, the capability of hyperspectral airborne and simulated satellite data for SOC mapping and monitoring has been well demonstrated [22, 26]. Operational workflows already exist in some cases. The application of spaceborne hyperspectral imagery from missions such as PRISMA and EnMAP further confirms this potential [3, 18, 92, 126, 129, 169]. While the accuracy is increased compared to a multispectral mission, due to high spectral coverage and spectral resolution, the spatial and temporal coverage remain limited to a few study areas.

In summary, fully standardized delivery of SOC maps from EO is still under development. Continued advances in harmonized soil databases and hybrid modeling approaches that integrate physical and AI/ML methods are expected to reduce uncertainties. Therefore, we estimate the current TRL for SOC retrieval at 5–6.

Mineral composition and abundance

Imaging spectroscopy is a well-established technology for detecting and mapping surface mineralogy. Over recent decades, its use in geology and resource exploration has matured considerably, supported by extensive case studies in diverse geologic environments [4, 53, 108, 123]. Traditionally, spectroscopic data are processed to identify the dominant mineral phases within each pixel and to produce mineral classification maps. The VNIR region is primarily used to detect ferric (oxy)hydroxides, ferrous minerals, and rare earth elements, while the SWIR region is employed to identify carbonates, sulphates, clays, and other OH-bearing silicates. Beyond classification, these datasets allow the extraction of mineral abundance (e.g., kaolinite abundance) and compositional information (e.g., white mica compositional variations induced by Tschermak substitution), providing semi-quantitative estimates of mineral proportions and revealing the physicochemical conditions under which the minerals formed.

Despite its maturity, several challenges remain before imaging spectroscopy for geology and mineral exploration reaches full operational implementation. These include conducting studies in more diverse geological settings, developing quantitative mineral abundance retrieval methods, addressing spectral mixing effects, mitigating vegetation interference, capturing temporal changes in surface mineralogy, crucial for acid mine drainage monitoring, and demonstrating mapping capability from regional to country-wide scales.

We estimate the current TRL for geological and mineral mapping at 6, reflecting extensive testing under real-world conditions but incomplete operational standardization. Further validation across diverse geological contexts and refinement of quantitative workflows will be essential to reach higher TRLs with next-generation imaging spectroscopy missions.

Coloured fraction of dissolved organic carbon: CDOM

The coloured fraction of dissolved organic carbon (CDOM) is a key component of the aquatic carbon cycle. More than 90% of organic carbon in lakes is dissolved (DOC) [172], and the carbon outgassed from lakes annually exceeds the land–ocean flux [159]. As most DOC is spectrally not identifiable, detection relies on correlation with its coloured fraction, CDOM. Increasing CDOM (browning) influences water colour, light penetration, heating, stratification, and food web structure, and also poses challenges for drinking water production. CDOM and DOC mapping from remote sensing has been possible since the 1980s [111, 167]. Mapping is most successful where DOC and CDOM are strongly correlated, particularly in boreal lakes. Recent studies have tracked changes over decades across large areas, including China [116] and the world's largest lakes [112]. Global CDOM products from ESA's Lake-CCI are expected soon. We estimate the current TRL for CDOM and DOC mapping at 6, where a strong CDOM–DOC relationship exists. Achieving higher TRLs globally requires validation across diverse lake types, from clear alpine to dark boreal systems.

Phytoplankton functional types

Phytoplankton community composition strongly influences aquatic food webs, climate, and fisheries. Multispectral sensors have limited ability to detect functional types, whereas hyperspectral missions have demonstrated improved retrieval of pigment composition in coastal and inland waters [135]. Foundational work since the 1990s established principles for detecting phytoplankton pigments such as chlorophyll-a, chlorophyll-ab, and phycocyanin using hyperspectral data [60, 107, 157, 175]. Major challenges remain in atmospheric correction and developing algorithms that account for varied optical properties in different water types. Site-specific studies in coastal zones and lakes using hyperspectral HICO and PRISMA data demonstrate a TRL = 5 [62]. We estimate the current TRL at 5–6, with expectations to increase the TRL in the coming years as high-SNR data and global observations from the Plankton, Aerosol, Cloud, ocean Ecosystem mission (PACE) mission become available [25].

Shallow water mapping

Remote sensing has supported shallow water and benthic mapping since the 1990s, including seabed types, coral reefs, seagrass, and macrophytes [110]. Multispectral sensors (10–30 m resolution, or 1–2 m for WorldView) are well-suited but face limits in discriminating spectrally similar species. Most operational algorithms rely on airborne imaging spectroscopy, offering high spatial and spectral resolution but limited large-scale availability. Current demonstrations reach TRL = 5. Fusion methods combining 5 m panchromatic imagery with 30 m PRISMA hyperspectral cubes show promising improvements [112]. We estimate the present TRL for shallow water mapping at 5, with clear potential for advancement using forthcoming high-resolution hyperspectral missions.

Discussion and recommendations

By the mid-2030s, S2NG and CHIME are intended to provide a robust foundation for agricultural and environmental monitoring, policy compliance, and sustainable resource management, leveraging their complementary spectral, spatial, and temporal capabilities. The combination of AI-driven methodologies and strong user engagement in the development of tailored products will maximize the potential of these missions for both EU and global applications, ensuring close alignment with the EGD, new EU strategies, and likely also the UN SDGs.

The analysis across policy-relevant variables highlights distinct but complementary strengths of the upcoming missions. For forest and crop species identification, the enhanced spatial, temporal and spectral resolutions of

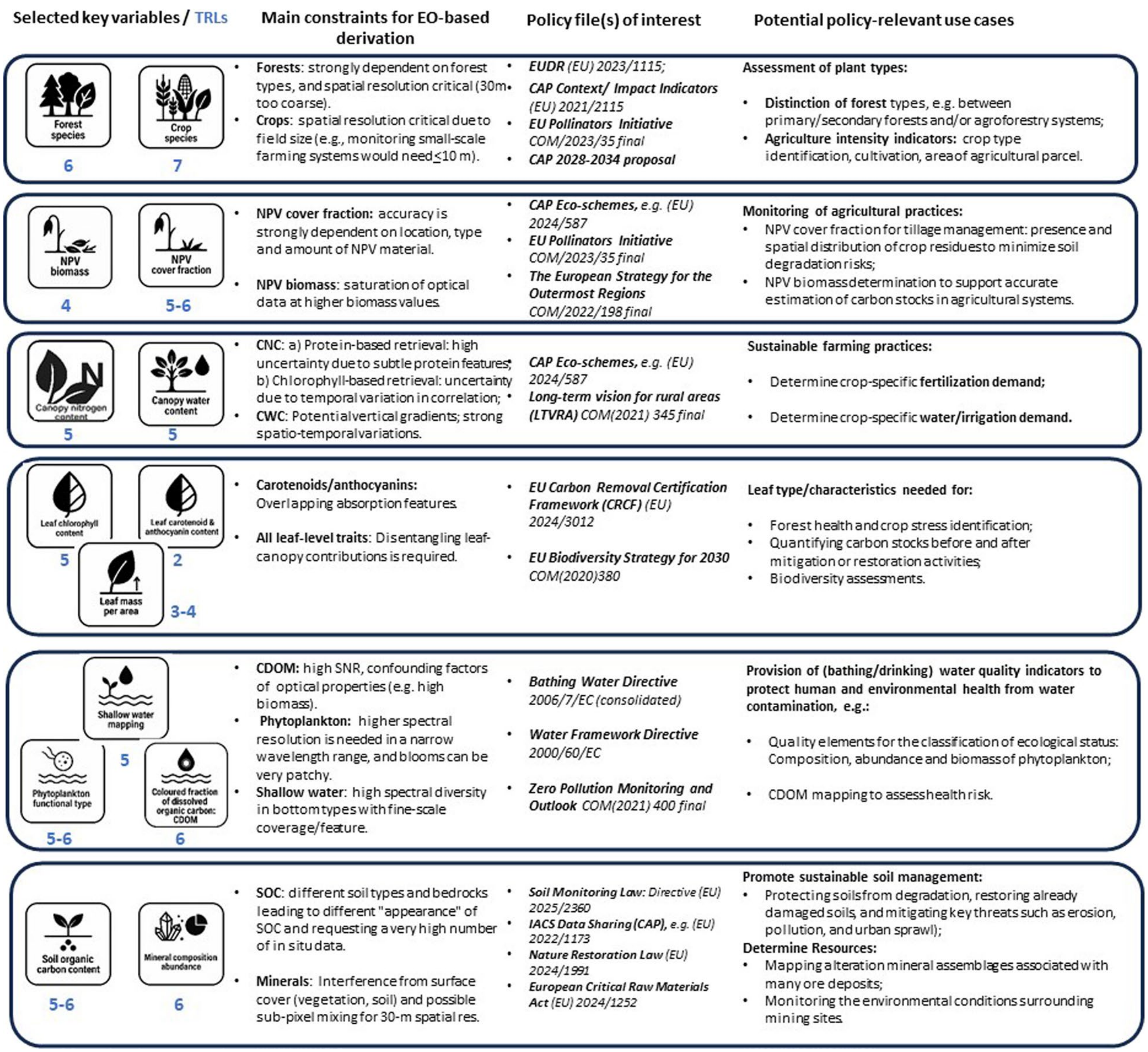

Fig. 4 Summary of key variables with their assessed actual TRLs, along with limitations when estimated from the future mission's data, policy files that could make use of the variables and potential policy-relevant use cases

S2NG are particularly critical, with 5–10 m data enabling sub-field to crown-scale mapping and generally outperforming 30 m sensors such as CHIME for species discrimination (e.g., [125]). CHIME's added value lies in its broad hyperspectral coverage, which is especially important for variables that strongly depend on SWIR information, such as NPV, LMA, and mineral mapping. Here, the combined spectral capabilities of CHIME and S2NG are expected to reduce retrieval uncertainties and raise the corresponding TRLs (e.g., [27, 82, 164]). CHIME will revolutionize large-scale SOC monitoring through precise spectral feature detection, while S2NG's enhanced temporal frequency will enable robust multitemporal compositing strategies that overcome current limitations in revisit time and bare soil availability, paving the way for operational, field-scale SOC mapping across Europe's agricultural landscapes [27, 169]. In shallow-water and aquatic ecosystem mapping, current PRISMA results suggest that hyperspectral cubes at CHIME-like resolutions can substantially improve fine-scale habitat and water-quality characterization, confirming the high potential of both CHIME and S2NG [112]. Although the LSTM mission's thermal imager constrains spatial resolution to 50 m, its observations can still effectively complement CHIME and S2NG by enabling crown-scale assessments of surface temperature and water-status indicators, thereby strengthening joint applications on vegetation stress, energy balance, and ecosystem functioning (e.g., [124, 131]). Looking ahead, synergistic use of S2NG and LSTM could further benefit from pan-sharpening approaches, where higher-resolution VIS–NIR–SWIR data from S2NG are used to sharpen LSTM thermal imagery, potentially enabling more effective variable estimation and mapping applications fulfilling policy needs.

In Fig. 4, we consolidate the 14 key variables examined in this study, outlining their primary limitations when derived from CHIME or S2NG, summarizing the relevant policy frameworks, and suggesting potential use cases to demonstrate practical applications.

In summary, from our investigations, we recommend the following technical advancements:

- Establishing EO time series and large area demonstrations for more robust retrieval assessments and to better track land dynamics with a focus on EGD policy requirements;
- Exploring scientific precursor missions data (EnMAP, PRISMA) to bring products to higher TRLs towards future service development and operational uptake;
- Developing and scaling of advanced processing and retrieval methodologies across a range of conditions and in EGD and actual EU priority areas;
- Enhancing and standardizing the in-situ component and ground/satellite data integrated analysis, required for robust calibration and validation of advanced methodologies;
- Exploration of synergies of future sensor systems, i.e., CHIME and S2NG, and other Sentinel next generation and expansion missions, such as LSTM, but also the Radar Observing System for Europe L-band (ROSE-L), complementing each other in spectral, temporal and spatial domains.

Most importantly, effective science-policy interfaces (SPIs) must be established to ensure that EO-derived research outputs (e.g., SOC or NPV maps) are translated into usable information for agricultural and environmental legislation. Such interfaces should promote co-design between scientists and policymakers, integrate policy-relevant validation metrics into research workflows, and foster continuous dialogue to bridge persisting TRL gaps that hinder operational and regulatory uptake.

In addition, successful policy uptake of EO-based products and services critically depends on early user engagement. Stakeholders' trust and acceptance grow in parallel with their active involvement in product development. Therefore, early consultation and co-design processes should form the foundation for advancing EO variables to higher TRLs, which can be effectively fostered, for instance, within EU Horizon and ESA project frameworks.

Conclusions

Upcoming spaceborne imaging spectroscopy with CHIME, together with advanced multispectral observations from S2NG expected in the early 2030s, will transform agricultural and environmental monitoring. Products derived from these missions will offer unprecedented traceability of key ecological processes, empowering the EU and its Member States to implement land-related policies with greater precision and accountability. To realize the EU's climate and sustainability ambitions, proactively integrating CHIME and S2NG capabilities into Copernicus products and services is essential. We strongly advocate for targeted research and innovation investments to advance the EO-based variables discussed in this study from prototype stages to full operational maturity. Establishing structured SPIs will be crucial in this process, enabling the translation of research outputs into actionable information for agricultural and environmental frameworks. These SPIs should emphasize co-production between scientists, policymakers, and service providers to align developments with regulatory needs and to bridge critical TRL gaps hindering operational uptake. Through strengthened dialogue and collaboration across these communities, the EU can harness next-generation EO data to deliver more advanced variables for land-related policies at both European and global scales.

Abbreviations

AECAs	Agri-environmental and climate actions
AGBD	Aboveground Biomass Density
ALS	Aerial laser scanner/Aerial laser scanning
AMSI	Advanced Multi-Spectral Instrument (on S2NG)
ARD	Analysis Ready Data
CAP	Common Agricultural Policy
CDOM	Coloured fraction of dissolved organic carbon
CHIME	Copernicus Hyperspectral Imaging Mission for the Environment
CLC	Corine Land Cover (if used in full text; appears via CLMS context)
CLMS	Copernicus Land Monitoring Service
CNC	Canopy nitrogen content
COP	Conference of the Parties (context: UN climate conferences)
CRCF	Carbon Removal Certification Framework
DABIS	Degressive Area-Based Income Support
DOC	Dissolved organic carbon
EC	European Commission
EEA	European Environment Agency / Exclusive Economic Areas
EGD	European Green Deal
EMIT	Earth Surface Mineral Dust Source Investigation (NASA imaging spectrometer)
EnMAP	Environmental Mapping and Analysis Program
EO	Earth Observation
ESA	European Space Agency
EU	European Union
EUDR	Regulation on deforestation-free products (EU Deforestation

	Regulation)
EUSO	EU Soil Observatory
EWT	Equivalent Water Thickness
fAPAR	Fraction of Absorbed Photosynthetically Active Radiation
GAEC	Good Agricultural and Environmental Conditions
GAI	Green Area Index
GHG	Greenhouse gas
IACS	Integrated Administration and Control System
JRC	Joint Research Centre (of the European Commission)
KCEO	Knowledge Centre on Earth Observation
LAI	Leaf Area Index
LFMC	Live fuel moisture content
LMA	Leaf mass per area
LSTM	Land Surface Temperature Monitoring (Copernicus mission)
LULUCF	Land Use, Land Use Change and Forestry
NFI	National Forest inventory
NIR	Near-infrared
NPV	Non-photosynthetic vegetation
NRR	Nature Restoration Regulation
PACE	Plankton, Aerosol, Cloud, ocean Ecosystem mission
PAI	Plant Area Index
PRISMA	PRecursore IperSpettrale della Missione Applicativa
RBMP	River Basin Management Plan
ROSE-L	Radar Observing System for Europe L-band
RTM	Radiative transfer model
S2	Sentinel-2 (first generation mission)
S2NG	Sentinel-2 Next Generation
SFM	Sustainable forest management
SNR	Signal-to-noise ratio
SOC	Soil organic carbon (content)
SPI	Science-Policy-Interface
SWIR	Shortwave infrared
TIR	Thermal infrared
TRL	Technology readiness level
UN	United Nations
VNIR	Visible-to-near infrared
WFD	Water Framework Directive

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Author contributions
KB conceived the study (conceptualization), designed the methodology, conducted the investigation and formal analysis, prepared visualizations, and wrote the original draft. PH contributed to the investigation and methodology and was a major contributor in writing the original draft. MS contributed to the methodology and to writing, review, and editing of the manuscript. MI contributed to visualizations, writing the original draft, and writing, review, and editing. ZS provided supervision, contributed to the methodology, and to writing, review, and editing. AO contributed to writing the original draft. SF contributed to conceptualization and writing the original draft. RC contributed to writing the original draft and to writing, review, and editing. CG contributed to writing the original draft. MM contributed to writing the original draft, writing, review, and editing, and to visualization. MW contributed to writing the original draft. PD contributed to writing, review, and editing. TK contributed to writing the original draft and to writing, review, and editing. MF contributed to writing the original draft and to writing, review, and editing. JBF contributed to writing the original draft and to writing, review, and editing. SA contributed to writing the original draft. SC contributed to writing the original draft. HC contributed to writing the original draft. TS contributed to visualization. PR contributed to writing the original draft. CV contributed to writing, review, and editing. MC contributed to writing the original draft. SP contributed to writing the original draft. IJ contributed to writing, review, and editing. RM contributed to writing the original draft. AS contributed to writing, review, and editing. MH provided supervision, contributed to writing the original draft, and was responsible for project administration and funding acquisition. All authors read and approved the final manuscript.

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Availability of data and materials
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
During the preparation of this work, the author(s) used Perplexity in order to improve readability and language. After using these tools, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Competing interest
The authors declare no competing interests.

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References

1. Abdelbaki A, Milewski R, Saberioon M, Berger K, Demattê JAM, Chabrillat S (2025) Radiative transfer model-integrated approach for hyperspectral simulation of mixed soil-vegetation scenarios and soil organic carbon estimation. Remote Sens 17:2355. https://doi.org/10.3390/rs17142355
2. Amoli MG, Hasanlou M, Samadzadegan F, Taghizadeh-Mehrjardi R, Dadrass Javan F (2025) Estimating soil organic carbon using time series band 11 (SWIR) of multispectral Sentinel-2 satellite images and machine learning algorithms. Remote Sens Appl Soc Environ 40:101736. https://doi.org/10.1016/j.rsase.2025.101736
3. Angelopoulou T, Chabrillat S, Pignatti S, Milewski R, Karyotis K, Brell M, Ruhtz T, Bochtis D, Zalidis G (2023) Evaluation of airborne HySpex and spaceborne PRISMA hyperspectral remote sensing data for soil organic matter and carbonates estimation. Remote Sens 15:1106. https://doi.org/10.3390/rs15041106
4. Asadzadeh S, Zhou X, Chabrillat S (2024) Assessment of the spaceborne EnMAP hyperspectral data for alteration mineral mapping: a case study of the Reko Diq porphyry CuAu deposit, Pakistan. Remote Sens Environ 314:114389. https://doi.org/10.1016/j.rse.2024.114389
5. Asam S, Gessner U, Almengor Gonzalez R, Wenzl M, Kriese J, Kuenzer C (2022) Mapping crop types of Germany by combining temporal statistical metrics of Sentinel-1 and Sentinel2 time series with LPIS data. Remote Sens 14:2981. https://doi.org/10.3390/rs14132981
6. Asner GP, Heidebrecht KB (2002) Spectral unmixing of vegetation, soil and dry carbon cover in arid regions: comparing multispectral and hyperspectral observations. Int J Remote Sens 23:3939–3958. https://doi.org/10.1080/01431160110115960
7. Asner GP, Martin RE, Anderson CB, Knapp DE (2015) Quantifying forest canopy traits: imaging spectroscopy versus field survey. Remote Sens Environ 158:15–27. https://doi.org/10.1016/j.rse.2014.11.011
8. Bachmann M, Alonso K, Carmona E, Gerasch B, Habermeyer M, Holzwarth S, Krawczyk H, Langheinrich M, Marshall D, Pato M, Pinnel N, de losReyes R, Schneider M, Schwind P, Storch T (2021) Analysis-Ready data from hyperspectral sensors—the design of the EnMAP CARD4L-SR data product. Remote Sens 13:4536. https://doi.org/10.3390/rs13224536
9. Bannari A, Pacheco A, Staenz K, McNairn H, Omari K (2006) Estimating and mapping crop residues cover on agricultural lands using hyperspectral and IKONOS data. Remote Sens Environ 104:447–459. https://doi.org/10.1016/j.rse.2006.05.018
10. Ben-Dor, E.I., J.R. and Epema, G.F. (1999). Soil Reflectance. Remote Sensing for the Earth Sciences: Manual of Remote Sensing (pp. 111–188). New York: John Wiley & Sons
11. Berger K, Foerster S, Szantoi Z, Hostert P, Foerster M, Van De Kerchove R, Vancutsem C, Schweitzer C, Masolele R, Reiche J, Dowell M, Enssle F, Suarez DR, Nepomshina O, Herold M (2025) Evolving earth observation capabilities for recent land-related EU policies. Land Use Policy 158:107749. https://doi.org/10.1016/j.landusepol.2025.107749
12. Berger K, Hank T, Halabuk A, Rivera-Caicedo JP, Wocher M, Mojses M, Gerhatova K, Tagliabue G, Dolz MM, Venteo ABP, Verrelst J (2021) Assessing non-photosynthetic cropland biomass from spaceborne hyperspectral imagery. Remote Sens 13:4711. https://doi.org/10.3390/rs13224711
13. Berger K, Verrelst J, F´eret JB, Hank T, Wocher M, Mauser W, Camps-Valls G (2020) Retrieval of aboveground crop nitrogen content with a hybrid machine learning method. Int J Appl Earth Obs Geoinf 92:102174. https://doi.org/10.1016/j.jag.2020.102174
14. Berger K, Verrelst J, F´eret JB, Wang Z, Wocher M, Strathmann M, Danner M, Mauser W, Hank T (2020) Crop nitrogen monitoring: recent progress and principal developments in the context of imaging spectroscopy missions. Remote Sens Environ 242:111758. https://doi.org/10.1016/j.rse.2020.111758
15. Blickensdörfer L, Oehmichen K, Pflugmacher D, Kleinschmit B, Hostert P (2024) National tree species mapping using sentinel-1/2 time series and German national forest inventory data. Remote Sens Environ 304:114069
16. Bontemps, S., 2022. Sen4cap - Sentinels for Common Agricultural Policy. URL:https://www.esa-sen4cap.org/ [Online; accessed 15. Sep. 2025].
17. Bossung C, Schlerf M, Machwitz M (2022) Estimation of canopy nitrogen content in winter wheat from Sentinel-2 images for operational agricultural monitoring. Precis Agric 23:2229–2252. https://doi.org/10.1007/s11119-022-09918-y
18. Bouslihim Y, Bouasria A (2025) Potential of EnMAP hyperspectral imagery for regional-scale soil organic matter mapping. Remote Sens 17:1600. https://doi.org/10.3390/rs17091600
19. Breidenbach J, Waser LT, Debella-Gilo M, Schumacher J, Rahlf J, Hauglin M, Puliti S, Astrup R (2021) National mapping and estimation of forest area by dominant tree species using Sentinel-2 data. Can J Forest Res 51:365–379. https://doi.org/10.1139/cjfr-2020-0170
20. Buschkamp P, Sang B, Peacocke P, Pieraccini S, Geiss MJ, Roth C, Moreau V, Borguet B, Maresi L, Rast M, Nieke J (2021) Chime's hyperspectral imaging spectrometer design result from phase a/b1. SPIE-Intl Soc Optical Eng. https://doi.org/10.1117/122599428
21. Camia, A., Gliottone, I., Dowell, M., Gilmore, R., Coll, M., Skidmore, A., Chirici, G., Caimi, C., Brink, A., Robuchon, M., Ferrario, I., 2023. Earth observation in support of EU policies for biodiversity: a deep-dive assessment of the Knowledge Centre on Earth Observation. Publications Office of the EU URL: https://op.europa.eu/en/publication-detail/-/publication/bb713e80-e316-11ed-a05c-01aa75ed71a1/language-en, https://doi.org/10.2760/185588.
22. Castaldi F, Chabrillat S, van Wesemael B (2019) Sampling strategies for soil property mapping using multispectral Sentinel-2 and hyperspectral EnMAP satellite data. Remote Sens 11:309. https://doi.org/10.3390/rs11030309
23. Ceccato P, Flasse S, Tarantola S, Jacquemoud S, Grégoire JM (2001) Detecting vegetation leaf water content using reflectance in the optical domain. Remote Sens Environ 77:22–33. https://doi.org/10.1016/S0034-4257(01)00191-2
24. Celesti, M., Rast, M., Adams, J., Boccia, V., Gascon, F., Isola, C., Nieke, J., 2022. The Copernicus hyperspectral imaging mission for the environment (CHIME): Status and planning, in: IGARSS 2022–2022 IEEE International Geoscience and Remote Sensing Symposium, IEEE. pp. 5011–5014.
25. Cetinic I, Rousseaux CS, Carroll IT, Chase AP, Kramer SJ, Werdell PJ, Siegel DA, Dierssen HM, Catlett D, Neeley A, Soto Ramos IM, Wolny JL, Sadoff N, Urquhart E, Westberry TK, Stramski D, Pahlevan N, Seegers BN, Sirk E, Lange PK, Vandermeulen RA, Graff JR, Allen JG, Gaube P, McKinna LIW, McKibben SM, Binding CE, Calzado VS, Sayers M (2024) Phytoplankton composition from sPACE: requirements, opportunities, and challenges. Remote Sens Environ 302:113964. https://doi.org/10.1016/j.rse.2023.113964
26. Chabrillat S, Ben-Dor E, Cierniewski J, Gomez C, Schmid T, van Wesemael B (2019) Imaging spectroscopy for soil mapping and monitoring. Surv Geophys 40:361–399. https://doi.org/10.1007/s10712-019-09524-0
27. Chabrillat S, Foerster S, Segl K, Beamish A, Brell M, Asadzadeh S, Milewski R, Ward KJ, Brosinsky A, Koch K, Scheffler D, Guillaso S, Kokhanovsky A, Roessner S, Guanter L, Kaufmann H, Pinnel N, Carmona E, Storch T, Hank T, Berger K, Wocher M, Hostert P, van der Linden S, Okujeni A, Janz A, Jakimow B, Bracher A, Soppa MA, Alvarado LMA, Buddenbaum H, Heim B, Heiden U, Moreno J, Ong C, Bohn N, Green RO, Bachmann M, Kokaly R, Schodlok M, Painter TH, Gascon F, Buongiorno F, Mottus M, Brando VE, Feilhauer H, Betz M, Baur S, Feckl R, Schickling A, Krieger V, Bock M, La Porta L, Fischer S (2024) The EnMAP spaceborne imaging spectroscopy mission: initial scientific results two years after launch. Remote Sens Environ 315:114379. https://doi.org/10.1016/j.rse.2024.114379
28. Chadwick KD, Brodrick PG, Grant K, Goulden T, Henderson A, Falco N, Wainwright H, Williams KH, Bill M, Breckheimer I, Brodie EL, Steltzer H, Williams CFR, Blonder B, Chen J, Dafflon B, Damerow J, Hancher M, Khurram A, Lamb J, Lawrence CR, McCormick M, Musinsky J, Pierce S, Polussa A, Hastings Porro M, Scott A, Singh HW, Sorensen PO, Varadharajan C, Whitney B, Maher K (2020) Integrating airborne remote sensing and field campaigns for ecology and earth system science. Methods Ecol Evol 11:1492–1508. https://doi.org/10.1111/2041-210X.13463
29. Clevers JGPW, Kooistra L, Van den Brande MMM (2017) Using Sentinel-2 data for retrieving lai and leaf and canopy chlorophyll content of a potato crop. Remote Sens 9:405. https://doi.org/10.3390/rs9050405
30. Commission, E., 2000. Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000 establishing a framework for

Community action in the field of water policy. URL: https://eur-lex.europa.eu/eli/dir/2000/60/oj [Online; accessed 16. Dec. 2025].
31. Commission, E., 2006. DIRECTIVE 2006/7/EC OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 15 February 2006 concerning the management of bathing water quality and repealing Directive 76/160/EEC. URL: https://eur-lex.europa.eu/legal-content/EN/%20TXT/HTML/?uri=CELEX:02006L0007-20140101, [Online; accessed 17. Dec. 2025].
32. Commission, E., 2019a. COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS Stepping up EU Action to Protect and Restore the World's Forests. COM/2019/352 final. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=%20CELEX%3A52019DC0352, [Online; accessed 17. Dec. 2025].
33. Commission, E., 2019b. COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE EUROPEAN COUNCIL, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS The European Green Deal. COM/2019/640 final. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1576150542719&uri=COM%3A2019%3A640%3AFIN, [Online; accessed 17. Dec. 2025].
34. Commission, E., 2019c. COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS Stepping up EU Action to Protect and Restore the World's Forests. SWD(2019) 307 final. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52019DC0352, [Online; accessed 17. Dec. 2025].
35. Commission, E., 2020a. COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS A Farm to Fork Strategy for a fair, healthy and environmentally-friendly food system. COM/2020/381 final. URL: https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX%3A52020DC0381, [Online; accessed 17. Dec. 2025].
36. Commission, E., 2020b. COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS Critical Raw Materials Resilience: Charting a Path towards greater Security and Sustainability. COM/2020/474 final. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0474, [Online; accessed 17. Dec. 2025].
37. Commission, E., 2020c. COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS EU Biodiversity Strategy for 2030 Bringing nature back into our lives. COM/2020/380 final. URL:https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=%20CELEX%3A52020DC0380&qid=1717751419906, [Online; accessed 17. Dec. 2025].
38. Commission, E., 2021a. COMMISSION STAFF WORKING DOCUMENT Sustainable carbon cycles - Carbon farming Accompanying the Communication from the Commission to the European Parliament and the Council Sustainable Carbon Cycles. SWD/2021/450 final. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52021SC0450, [Online; accessed 17. Dec. 2025].
39. Commission, E., 2021b. COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS EU Soil Strategy for 2030 Reaping the benefits of healthy soils for people, food, nature and climate. COM/2021/699 final. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:52021DC0699, [Online; accessed 17. Dec. 2025].
40. Commission, E., 2021c. COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS Forging a climate-resilient Europe - the new EU Strategy on Adaptation to Climate Change. COM/2021/82 final. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=COM%3A2021%3A82%3AFIN, [Online; accessed 17. Dec. 2025].
41. Commission, E., 2021d. COMMUNICATION FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT, THE COUNCIL, THE EUROPEAN ECONOMIC AND SOCIAL COMMITTEE AND THE COMMITTEE OF THE REGIONS New EU Forest Strategy for 2030. COM/2021/572 final. URL:https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=COM%3A2021%3A572%3AFIN, [Online; accessed 17. Dec. 2025].
42. Commission, E., 2022. DIRECTIVE OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL amending Directive 2000/60/EC establishing a framework for Community action in the field of water policy, Directive 2006/118/EC on the protection of groundwater against pollution and deterioration and Directive 2008/105/EC on environmental quality standards in the field of water policy. COM/2022/540 final. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52022PC0540, [Online; accessed 17. Dec. 2025].
43. Commission, E., 2023a. Proposal for a REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL on a monitoring framework for resilient European forests. COM/2023/728 final. URL:https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:52023PC0728, [Online; accessed 17. Dec. 2025].
44. Commission, E., 2023b. REGULATION (EU) 2023/839 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 19 April 2023 amending Regulation (EU) 2018/841 as regards the scope, simplifying the reporting and compliance rules, and setting out the targets of the Member States for 2030, and Regulation (EU) 2018/1999 as regards improvement in monitoring, reporting, tracking of progress and review. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/%20HTML/?uri=CELEX:32023R0839, [Online; accessed 17. Dec. 2025].
45. Commission, E., 2023c. REPORT FROM THE COMMISSION TO THE EUROPEAN PARLIAMENT AND THE COUNCIL Summary of CAP Strategic Plans for 2023–2027: joint effort and collective ambition. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52023DC0707&qid=1740291377905, Online; accessed 17. Dec. 2025].
46. Commission, E., 2024. REGULATION (EU) 2024/1252 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 11 April 2024 establishing a framework for ensuring a secure and sustainable supply of critical raw materials and amending Regulations (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1724 and (EU) 2019/1020. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=OJ:L_202401252, [Online; accessed 17. Dec. 2025].
47. Commission, E., 2025a. Commission simplifies Common Agricultural Policy to support farmers and enhance competitiveness. URL: https://ec.europa.eu/commission/presscorner/detail/en/ip_25_1205, [Online; accessed 17. Dec. 2025].
48. Commission, E., 2025b. A fairer, better targeted income support for farmers: The CAP 2028–2034 proposal explained. URL: https://agriculture.ec.europa.eu/document/download/9ec9d9ae-2d40-4549-bf20-943f7f5854f8_en?filename=factsheet-europe-budget-fairer-income-farmers_en.pdf, [Online; accessed 17. Dec. 2025].
49. Cornelissen JHC, Grootemaat S, Verheijen LM, Cornwell WK, van Bodegom PM, van der Wal R, Aerts R (2017) Are litter decomposition and fire linked through plant species traits? New Phytol 216:653–669. https://doi.org/10.1111/nph.14766
50. Cramer MD, Hawkins HJ, Verboom GA (2009) The importance of nutritional regulation of plant water flux. Oecologia 161:15–24. https://doi.org/10.1007/s00442-009-1364-3
51. Croft H, Chen J, Wang R, Mo G, Luo S, Luo X, He L, Gonsamo A, Arabian J, Zhang Y, Simic-Milas A, Noland T, He Y, Homolová L, Malenovsky Z, Yi Q, Beringer J, Amiri R, Hutley L, Arellano P, Stahl C, Bonal D (2020) The global distribution of leaf chlorophyll content. Remote Sens Environ 236:111479. https://doi.org/10.1016/j.rse.2019.111479
52. Croft, H., Chen, J.M., & Berger, K. (2026). 3.06 - Remote Sensing of Leaf Pigment Content. In S. Liang (Ed.), Comprehensive Remote Sensing (Second Edition) (pp. 100–132). Oxford: Elsevier. https://doi.org/10.1016/B978-0-443-13220-9.00085-8.
53. Cudahy T (2016) Mineral mapping for exploration: an Australian journey of evolving spectral sensing technologies and industry collaboration. Geosciences 6:52. https://doi.org/10.3390/geosciences6040052
54. Curran PJ (1989) Remote sensing of foliar chemistry. Remote Sens Environ 30:271–278. https://doi.org/10.1016/0034-4257(89)90069-2
55. Curran PJ, Dungan JL, Gholz HL (1990) Exploring the relationship between reflectance red edge and chlorophyll content in slash pine. Tree Physiol 7:33–48. https://doi.org/10.1093/treephys/7.1-2-3-4.33

56. Daryaei A, Lechner M, Iglseder A, Waser LT, Immitzer M (2025) Sentinel-2 vs. PlanetScope: comparison and combination for tree species classification in two central European forest ecosystems. Remote Sens Appl: Soc Environ 38:101617. https://doi.org/10.1016/j.rsase.2025.101617
57. Daughtry C, Walthall C, Kim M, Brown de Colstoun E, McMurtrey J (2000) Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. Remote Sens Environ 74:229–239. https://doi.org/10.1016/S0034-4257(00)00113-9
58. De Clerck E, Kováacs D, Berger K, Schlerf M, Verrelst J (2024) Optimizing hybrid models for canopy nitrogen mapping from Sentinel-2 in Google Earth Engine. ISPRS J Photogramm Remote Sens 218:530–545. https://doi.org/10.1016/j.isprsjprs.2024.11.005
59. De Vroey M, de Vendictis L, Zavagli M, Bontemps S, Heymans D, Radoux J, Koetz B, Defourny P (2022) Mowing detection using Sentinel-1 and Sentinel-2 time series for large scale grassland monitoring. Remote Sens Environ 280:113145. https://doi.org/10.1016/j.rse.2022.113145
60. Dekker, A.G., 1993. Detection of optical water quality parameters for eutrophic waters by high resolution remote sensing. Vrije Universiteit Amsterdam URL: https://research.vu.nl/en/ publications/detection-of-optical-water-quality-parameters-for-eutrophic-water.
61. Dematte JAM, Rizzo R, Rosin NA, Poppiel RR, Novais JJM, Amorim MTA, Rodriguez-Albarrac´ın HS, Rosas JTF, Bartsch BdA, Vogel LG, Minasny B, Grunwald S, Ge Y, Ben-Dor E, Gholizadeh A, Gomez C, Chabrillat S, Francos N, Fiantis D, Belal A, Tsakiridis N, Kalopesa E, Naimi S, Ayoubi S, Tziolas N, Das BS, Zalidis G, Francelino MR, Mello DCd, Hafshejani NA, Peng Y, Ma Y, Coblinski JA, Wadoux AMJC, Savin I, Malone BP, Karyotis K, Milewski R, Vaudour E, Wang C, Salama ESM, Shepherd KD (2025) A global soil spectral grid based on space sensing. Sci Total Environ 968:178791. https://doi.org/10.1016/j.scitotenv.2025.178791
62. Dierssen H, Bracher A, Brando V, Loisel H, Ruddick K (2020) Data needs for hyperspectral detection of algal diversity across the globe. Oceanography 33:74–79. https://doi.org/10.5670/oceanog.2020.111
63. Drusch M, Del Bello U, Carlier S, Colin O, Fernandez V, Gascon F, Hoersch B, Isola C, Laberinti P, Martimort P, Meygret A, Spoto F, Sy O, Marchese F, Bargellini P (2012) Sentinel-2: ESA's optical high-resolution mission for GMES operational services. Remote Sens Environ 120:25–36. https://doi.org/10.1016/j.rse.2011.11.026
64. Duveiller G, Baret F, Defourny P (2011) Crop specific green area index retrieval from MODIS data at regional scale by controlling pixel-target adequacy. Remote Sens Environ 115:2686–2701. https://doi.org/10.1016/j.rse.2011.05.026
65. Duveiller G, Defourny P (2010) A conceptual framework to define the spatial resolution requirements for agricultural monitoring using remote sensing. Remote Sens Environ 114:2637–2650. https://doi.org/10.1016/j.rse.2010.06.001
66. Dvorakova K, Heiden U, Pepers K, Staats G, van Os G, van Wesemael B (2023) Improving soil organic carbon predictions from a Sentinel–2 soil composite by assessing surface conditions and uncertainties. Geoderma 429:116128. https://doi.org/10.1016/j.geoderma.2022.116128
67. EEA, 2020. State of nature in the EU, Results from reporting under the nature directives 20132018. Technical Report. URL: https://www.eea.europa.eu/en/analysis/publications/state-of-nature-in-the-eu-2020. [Online; accessed 17. Dec. 2025].
68. Elsayed S, Elhoweity M, Ibrahim HH, Dewir YH, Migdadi HM, Schmidhalter U (2017) Thermal imaging and passive reflectance sensing to estimate the water status and grain yield of wheat under different irrigation regimes. Agric Water Manage 189:98–110. https://doi.org/10.1016/j.agwat.2017.05.001
69. Elvidge CD (1990) Visible and near infrared reflectance characteristics of dry plant materials. Int J Remote Sens 11:1775–1795. https://doi.org/10.1080/01431169008955129.
70. ESA, 2008. Technology Readiness levels handbook for space applications. Technical Report. European Space Agency. TEC-SHS/5551/MG/ap. September 2008.
71. Estévez J, Salinero-Delgado M, Berger K, Pipia L, Rivera-Caicedo JP, Wocher M, Reyes Muñoz P, Tagliabue G, Boschetti M, Verrelst J (2022) Gaussian processes retrieval of crop traits in Google Earth Engine based on Sentinel-2 top-of-atmosphere data. Remote Sens Environ 273:112958. https://doi.org/10.1016/j.rse.2022.112958
72. EU, 2021a. European Climate Law: SUMMARY OF: Regulation (EU) 2021/1119 establishing the framework for achieving climate neutrality and amending Regulations (EC) No 401/2009 and (EU) 2018/1999 ('European Climate Law') WHAT IS THE AIM OF THE REGULATION? URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=LEGISSUM:4536626, [Online; accessed 17. Dec. 2025].
73. EU, 2021b. REGULATION (EU) 2021/2115 of the European Parliament and of the Council of 2 December 2021 establishing rules on support for strategic plans to be drawn up by Member States under the common agricultural policy (CAP Strategic Plans) and financed by the European Agricultural Guarantee Fund (EAGF) and by the European Agricultural Fund for Rural Development (EAFRD) and repealing Regulations (EU) No 1305/2013 and (EU) No 1307/2013. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32021R2115, [Online; accessed 17. Dec. 2025].
74. EU, 2021c. Regulation (EU) 2021/696 of the European Parliament and of the Council of 28 April 2021 establishing the Union Space Programme and the European Union Agency for the Space Programme and repealing Regulations (EU) No 912/2010, (EU) No 1285/2013 and (EU) No 377/2014 and Decision No 541/2014/EU. URL: https://eur-lex.europa.eu/eli/reg/2021/696/oj/eng, [Online; accessed 17. Dec. 2025].
75. EU, 2023. Regulation (EU) 2023/1115 of the European Parliament and of the Council of 31 May 2023 on the making available on the Union market and the export from the Union of certain commodities and products associated with deforestation and forest degradation and repealing Regulation (EU) No 995/2010 (Text with EEA relevance). URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32023R1115&qid=1687867231461, [Online; accessed 17. Dec. 2025].
76. EU, 2024a. REGULATION (EU) 2024/1991 of the European Parliament and of the Council of 24 June 2024 on nature restoration and amending Regulation (EU) 2022/869 (Text with EEA relevance). URL: https://eur-lex.europa.eu/eli/reg/2024/1991/oj/eng, [Online; accessed 17. Dec. 2025].
77. EU, 2024b. REGULATION (EU) 2024/3012 of the European Parliament and of the Council of 27 November 2024 establishing a Union certification framework for permanent carbon removals, carbon farming and carbon storage in products. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32024R3012&qid=1738863340072, [Online; accessed 17. Dec. 2025].
78. EU, 2025. Directive (EU) 2025/2360 of the European Parliament and of the Council of 12 November 2025 on soil monitoring and resilience (Soil Monitoring Law). URL: https://eur-lex.europa.eu/eli/dir/2025/2360/oj/eng, [Online; accessed 17. Dec. 2025].
79. Fassnacht FE, Latifi H, Sterenczak K, Modzelewska A, Lefsky M, Waser LT, Straub C, Ghosh A (2016) Review of studies on tree species classification from remotely sensed data. Remote Sens Environ 186:64–87. https://doi.org/10.1016/j.rse.2016.08.013.
80. Féret JB, Berger K, de Boissieu F, Malenovsky Z (2021) PROSPECT-PRO for estimating content of nitrogen-containing leaf proteins and other carbon-based constituents. Remote Sens Environ 252:112173. https://doi.org/10.1016/j.rse.2020.112173.
81. Féret JB, Gitelson AA, Noble SD, Jacquemoud S (2017) PROSPECT-D: towards modeling leaf optical properties through a complete lifecycle. Remote Sens Environ 193:204–215. https://doi.org/10.1016/j.rse.2017.03.004.
82. Féret JB, le Maire G, Jay S, Berveiller D, Bendoula R, Hmimina G, Cheraiet A, Oliveira J, Ponzoni F, Solanki T, de Boissieu F, Chave J, Nouvellon Y, Porcar-Castell A, Proisy C, Soudani K, Gastellu-Etchegorry JP, Lefevre-Fonollosa MJ (2019) Estimating leaf mass per area and equivalent water thickness based on leaf optical properties: potential and limitations of physical modeling and machine learning. Remote Sens Environ 231:110959. https://doi.org/10.1016/j.rse.2018.11.002
83. Fourty T, Baret F, Jacquemoud S, Schmuck G, Verdebout J (1996) Leaf optical properties with explicit description of its biochemical composition: direct and inverse problems. Remote Sens Environ 56:104–117. https://doi.org/10.1016/0034-4257(95)00234-0
84. Fu Y, Yang G, Pu R, Li Z, Li H, Xu X, Song X, Yang X, Zhao C (2021) An overview of crop nitrogen status assessment using hyperspectral remote sensing: current status and perspectives. Eur J Agron 124:126241. https://doi.org/10.1016/j.eja.2021.126241
85. Gara TW, Darvishzadeh R, Skidmore AK, Wang T, Heurich M (2019) Accurate modelling of canopy traits from seasonal Sentinel-2 imagery based

on the vertical distribution of leaf traits. ISPRS J Photogramm Remote Sens 157:108–123. https://doi.org/10.1016/j.isprsjprs.2019.09.005
86 Gara TW, Rahimzadeh-Bajgiran P, Darvishzadeh R (2021) Forest leaf mass per area (lma) through the eye of optical remote sensing: A review and future outlook. Remote Sens. https://doi.org/10.3390/rs13173352
87 Gentine P, Green JK, Gu´erin, M., Humphrey, V., Seneviratne, S.I., Zhang, Y., Zhou, S., (2019) Coupling between the terrestrial carbon and water cycles—a review. Environ Res Lett 14:083003. https://doi.org/10.1088/1748-9326/ab22d6
88. Ghassemi B, Dujakovic A, Zóltak M, Immitzer M, Atzberger C, Vuolo F (2022) Designing˙ a European-wide crop type mapping approach based on machine learning algorithms using LUCAS field survey and Sentinel-2 data. Remote Sens 14(3):541. https://doi.org/10.3390/rs14030541
89. Ghiyamat A, Shafri HZM, Amouzad Mahdiraji G, Shariff ARM, Mansor S (2013) Hyperspectral discrimination of tree species with different classifications using single- and multipleendmember. Int J Appl Earth Obs Geoinf 23:177–191. https://doi.org/10.1016/j.jag.2013.01.004
90. Grabska E, Frantz D, Ostapowicz K (2020) Evaluation of machine learning algorithms for forest stand species mapping using Sentinel-2 imagery and environmental data in the Polish Carpathians. Remote Sens Environ 251:112103. https://doi.org/10.1016/j.rse.2020.112103
91. Grabska-Szwagrzyk E, Tiede D, Sudmanns M, Kozak J (2024) Map of forest tree species for Poland based on Sentinel-2 data. Earth Syst Sci Data 16:2877–2891. https://doi.org/10.5194/essd-16-2877-2024
92. Guillaso, S., Segl, K., Asadzadeh, S., Milewski, R., Pignatti, S., Musacchio, M., Sánchez Montero, A.M., Chabrillat, S., 2023. Developments of l2b soil and mineral products in the frame of the development of the CHIME-e2e simulator, in: IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium, pp. 1249–1252. https://doi.org/10.1109/IGARSS52108.2023.
93. Guo Y, Mokany K, Ong C, Moghadam P, Ferrier S, Levick SR (2023) Plant species richness prediction from DESIS hyperspectral data: a comparison study on feature extraction procedures and regression models. ISPRS J Photogramm Remote Sens 196:120–133. https://doi.org/10.1016/j.isprsjprs.2022.12.028
94. Hauser LT, Féret JB, An Binh N, van der Windt N, Sil AF, Timmermans J, ˆ Soudzilovskaia, N.A., van Bodegom, P.M., (2021) Towards scalable estimation of plant functional diversity from Sentinel-2: In-situ validation in a heterogeneous (semi-)natural landscape. Remote Sens Environ 262:112505. https://doi.org/10.1016/j.rse.2021.112505
95. Hemmerling J, Pflugmacher D, Hostert P (2021) Mapping temperate forest tree species using dense Sentinel-2 time series. Remote Sens Environ 267:112743. https://doi.org/10.1016/j.rse.2021.112743
96. Hill MJ, Guerschman JP (2020) The MODIS global vegetation fractional cover product 2001–2018: characteristics of vegetation fractional cover in grasslands and savanna woodlands. Remote Sens 12:406. https://doi.org/10.3390/rs12030406
97. Hively WD, Lamb BT, Daughtry CST, Serbin G, Dennison P, Kokaly RF, Wu Z, Masek JG (2021) Evaluation of SWIR crop residue bands for the Landsat Next Mission. Remote Sens 13:3718. https://doi.org/10.3390/rs13183718
98. Homolová L, Malenovsky Z, Clevers JGPW, Garc´ıa-Santos, G., Schaepman, M.E., (2013) Review of optical-based remote sensing for plant trait mapping. Ecol Compl 15:1–16. https://doi.org/10.1016/j.ecocom.2013.06.003
99. Immitzer M, Atzberger C, Koukal T (2012) Tree species classification with Random Forest using very high spatial resolution 8-band WorldView-2 satellite data. Remote Sens 4:2661–2693. https://doi.org/10.3390/rs4092661
100. Immitzer M, Neuwirth M, Böck S, Brenner H, Vuolo F, Atzberger C (2019) Optimal input features for tree species classification in Central Europe based on multi-temporal Sentinel-2 data. Remote Sens 11:2599. https://doi.org/10.3390/rs11222599
101. Kalantari Z, Ferreira CSS, Pan H, Pereira P (2023) Nature-based solutions to global environmental challenges. Sci Total Environ 880:163227. https://doi.org/10.1016/j.scitotenv.2023.163227
102. KCEO, 2025. Supporting policy with scientific evidence: EU Policy Areas. URL: https://knowledge4policy.ec.europa.eu/earth-observation/eu%C2%A0policy-areas_en, [Online; accessed 17. Dec. 2025].
103. Kokaly RF, Asner GP, Ollinger SV, Martin ME, Wessman CA (2009) Characterizing canopy biochemistry from imaging spectroscopy and its application to ecosystem studies. Remote Sens Environ 113:S78–S91. https://doi.org/10.1016/j.rse.2008.10.018
104. Konings AG, Saatchi SS, Frankenberg C, Keller M, Leshyk V, Anderegg WRL, Humphrey V, Matheny AM, Trugman A, Sack L, Agee E, Barnes ML, Binks O, Cawse-Nicholson K, Christoffersen BO, Entekhabi D, Gentine P, Holtzman NM, Katul GG, Liu Y, Longo M, Martinez-Vilalta J, McDowell N, Meir P, Mencuccini M, Mrad A, Novick KA, Oliveira RS, Siqueira P, Steele-Dunne SC, Thompson DR, Wang Y, Wehr R, Wood JD, Xu X, Zuidema PA (2021) Detecting forest response to droughts with global observations of vegetation water content. Global Change Biol 27:6005–6024. https://doi.org/10.1111/gcb.15872
105. Kopačková V, Ben-Dor E, Carmon N, Notesco G (2017) Modelling diverse soil attributes with visible to longwave infrared spectroscopy using PLSR employed by an automatic modelling engine. Remote Sensing 9:134. https://doi.org/10.3390/rs9020134
106. Kowalski K, Okujeni A, Hostert P (2023) A generalized framework for drought monitoring across Central European grassland gradients with Sentinel-2 time series. Remote Sens Environ 286:113449. https://doi.org/10.1016/j.rse.2022.113449
107. Kramer SJ, Siegel DA, Maritorena S, Catlett D (2022) Modeling surface ocean phytoplankton pigments from hyperspectral remote sensing reflectance on global scales. Remote Sens Environ 270:112879. https://doi.org/10.1016/j.rse.2021.112879
108. Kruse FA, Perry SL, Caballero A (2006) District-level mineral survey using airborne hyperspectral data, Los Menucos, Argentina. Ann Geophys. https://doi.org/10.4401/ag-3154
109. Kutser T (2004) Quantitative detection of chlorophyll in cyanobacterial blooms by satellite remote sensing. Limnol Oceanogr. https://doi.org/10.4319/lo.2004.49.6.2179
110. Kutser T, Hedley J, Giardino C, Roelfsema C, Brando VE (2020) Remote sensing of shallow waters—a 50 year retrospective and future directions. Remote Sens Environ 240:111619. https://doi.org/10.1016/j.rse.2019.111619
111. Kutser T, Herlevi A, Kallio K, Arst H (2001) A hyperspectral model for interpretation of passive optical remote sensing data from turbid lakes. Sci Total Environ 268:47–58. https://doi.org/10.1016/S0048-9697(00)00682-3
112. Kutser T, Soomets T (2024) Satellite data is revealing long time changes in the world largest lakes. Sci Rep 14:1–9. https://doi.org/10.1038/s41598-024-65250-7
113. Kutser T, Spyrakos E, WIlson, H., Tyler, A., Simis, S., Van Duibenbode, L., Reusen, I., Laas, A., Ioana, P., van Griensven, A., Escorihuela, M.J., Giardino, C., Bresciani, M., Pesquer Mayos, L., Ogashawara, I., Bassa, L., Thant, S., Walker, P., Van de Moortel, I., Constantinescu, A.M., Hunter, P., Nijs, K., Messens, F., Oloibiri, V., Henkens, S., Toming, K., Vahtm¨ae, E., Ligi, M., Soomets, T., Nejstgaard, J., Catianis, I., Dinu, I., Amditis, A., Tsiakos, V., Bliziotis, D., Costa, C., Jonoski, A., Pareeth, S., Gomes de Mesquita-Wever, R., Marconi, F., Bertini, C., Cremona, F., Kangro, K., Paun, M., Paun, A., Amarioarei, A., Milea, E., Weerasinghe, I., Chawanda, C., Baltodano, A., Sterckx, S., Knaeps, E., De Keukelaere, L., Hein, T., Feldbacher, E., Tschikof, M., Prat, E., Garc´ıa, C., Milcinski, G., Peters, S., Hommersom, A., Laanen, M., Cillero Castro, C., (2025) A roadmap for copernicus water services. Zenodo. https://doi.org/10.5281/zenodo.10847654
114. Li H, Yang W, Lei J, She J, Zhou X (2021) Estimation of leaf water content from hyperspectral data of different plant species by using three new spectral absorption indices. PLoS ONE 16:e0249351. https://doi.org/10.1371/journal.pone.0249351
115. Li J, Ge Y, Puntel LA, Heeren DM, Bai G, Balboa GR, Gamon JA, Arkebauer TJ, Shi Y (2024) Integrating UAV hyperspectral data and radiative transfer model simulation to quantitatively estimate maize leaf and canopy nitrogen content. Int J Appl Earth Obs Geoinf 129:103817. https://doi.org/10.1016/j.jag.2024.103817
116. Liu D, Shi K, Chen P, Yan N, Ran L, Kutser T, Tyler AN, Spyrakos E, Woolway RI, Zhang Y, Duan H (2024) Substantial increase of organic carbon storage in Chinese lakes. Nat Commun 15:8049. https://doi.org/10.1038/s41467-024-52387-2
117. Locherer M, Hank T, Danner M, Mauser W (2015) Retrieval of seasonal leaf area index from simulated EnMAP data through optimized

LUT-based inversion of the PROSAIL model. Remote Sens 7:10321–10346. https://doi.org/10.3390/rs70810321
118. Loozen Y, Rebel KT, de Jong SM, Lu M, Ollinger SV, Wassen MJ, Karssenberg D (2020) Mapping canopy nitrogen in European forests using remote sensing and environmental variables with the random forests method. Remote Sens Environ 247:111933. https://doi.org/10.1016/j.rse.2020.111933
119. Lopinto, E., Fasano, L., Longo, F., Sacco, P., 2022. Current Status of Prisma Mission, in: IGARSS 2022 2022 IEEE International Geoscience and Remote Sensing Symposium. IEEE. https://doi.org/10.1109/IGARSS46834.2022.9884414.
120. Ma H, Weiss M, Malik D, Berthelot B, Yebra M, Nolan RH, Mialon A, Zeng J, Quan X, Tagesson HT, Olioso A, Baret F (2025) Satellite canopy water content from Sentinel-2, Landsat-8 and Modis: principle, algorithm and assessment. Remote Sens Environ 326:114801. https://doi.org/10.1016/j.rse.2025.114801
121. Maschler J, Atzberger C, Immitzer M (2018) Individual tree crown segmentation and classification of 13 tree species using airborne hyperspectral data. Remote Sens 10:1218. https://doi.org/10.3390/rs10081218
122. Masolele RN, Marcos D, De Sy V, Abu IO, Verbesselt J, Reiche J, Herold M (2024) Mapping the diversity of land uses following deforestation across Africa. Sci Rep 14:1–16. https://doi.org/10.1038/s41598-024-52138-9
123. van der Meer FD, van der Werff HMA, van Ruitenbeek FJA, Hecker CA, Bakker WH, Noomen MF, van der Meijde M, Carranza EJM, Smeth, J.B.d., Woldai, T., (2012) Multi and hyperspectral geologic remote sensing: a review. Int J Appl Earth Obs Geoinf 14:112–128. https://doi.org/10.1016/j.jag.2011.08.002
124. Meerdink SK, Roberts DA, King JY, Roth KL, Dennison PE, Amaral CH, Hook SJ (2016) Linking seasonal foliar traits to VSWIR-TIR spectroscopy across California ecosystems. Remote Sens Environ 186:322–338. https://doi.org/10.1016/j.rse.2016.08.003
125. Meier J, Mauser W, Hank T, Bach H (2020) Assessments on the impact of high-resolution sensor pixel sizes for common agricultural policy and smart farming services in European regions. Comput Electron Agric 169:105205. https://doi.org/10.1016/j.compag.2019.105205
126. Milewski, R., Chabrillat, S., Tsakiridis, N.L., Tziolas, N., Schmid, T., 2024. Evaluation of EnMAP imagery for accurate topsoil estimation in Mediterranean agricultural regions, in: IGARSS 2024 - 2024 IEEE International Geoscience and Remote Sensing Symposium, pp. 1599–1602. doi:10.1109/IGARSS53475.2024.10642254. ISSN: 2153–7003.
127. Misurec, J., Dekanova, L., Roerink, G., Konata, P., Martinez, J., Stark, J., 2024. - The New CAP and Agriculture eco-schemes. D7 Algorithm Theoretical Basis Document GST-50222001-D2. Luxembourg (Luxembourg). URL: https://esa-people-ecoschemes.info/documentation. [Online; accessed 17. Dec. 2025].
128. Modzelewska A, Fassnacht FE, Sterenczak K (2020) Tree species identification within an extensive forest area with diverse management regimes using airborne hyperspectral data. Int J Appl Earth Obs Geoinf 84:101960. https://doi.org/10.1016/j.jag.2019.101960
129. Mzid N, Castaldi F, Tolomio M, Pascucci S, Casa R, Pignatti S (2022) Evaluation of agricultural bare soil properties retrieval from landsat 8, sentinel-2 and PRISMA satellite data. Remote Sens 14:714. https://doi.org/10.3390/rs14030714
130. Nagler P, Daughtry C, Goward S (2000) Plant litter and soil reflectance. Remote Sens Environ 71:207–215. https://doi.org/10.1016/S0034-4257(99)00082-6
131. Neinavaz E, Schlerf M, Darvishzadeh R, Gerhards M, Skidmore AK (2021) Thermal infrared remote sensing of vegetation: current status and perspectives. Int J Appl Earth Obs Geoinf 102:102415. https://doi.org/10.1016/j.jag.2021.102415
132. Nieke J, Despoisse L, Gabriele A, Weber H, Strese H, Ghasemi N, Gascon F, Alonso K, Boccia V, Tsonevska B, Choukroun P, Ottavianelli G, Celesti M (2023) The Copernicus hyperspectral imaging mission for the environment (chime): an overview of its mission, system and planning status. SPIE-Intl Soc Optical Eng. https://doi.org/10.1117/122679977
133. Niroumand-Jadidi M, Bovolo F, Bruzzone L (2020) Water quality retrieval from PRISMA hyperspectral images: first experience in a turbid lake and comparison with Sentinel-2. Remote Sens 12:3984. https://doi.org/10.3390/rs12233984
134. Okujeni A, Kowalski K, Lewinska KE, Schneidereit S, Hostert P (2024) Multidecadal grassland fractional cover time series retrieval for Germany from the Landsat and Sentinel-2 archives. Remote Sens Environ 302:113980. https://doi.org/10.1016/j.rse.2023.113980
135. O'Shea RE, Pahlevan N, Smith B, Bresciani M, Egerton T, Giardino C, Li L, Moore T, Ruiz-Verdu A, Ruberg S, Simis SGH, Stumpf R, Vaiciute D (2021) Advancing cyanobacteria biomass estimation from hyperspectral observations: demonstrations with HICO and PRISMA imagery. ODU Digital Commons. https://doi.org/10.1016/j.rse.2021.112693
136. Paleari S (2022) The impact of the European Green Deal on EU environmental policy. J Environ Dev 31:196–220. https://doi.org/10.1177/10704965221082222
137 Panagos P, Van Liedekerke M, Borrelli P, K¨oninger, J., Ballabio, C., Orgiazzi, A., Lugato, E., Liakos, L., Hervas, J., Jones, A., Montanarella, L. (2022) European Soil Data Centre 2.0: Soil data and knowledge in support of the EU policies. Eur J Soil Sci 73:e13315. https://doi.org/10.1111/ejss.13315
138. Pascual-Venteo AB, Portalés E, Berger K, Tagliabue G, Garcia JL, P´erez-Suay, A., Rivera-Caicedo, J.P., Verrelst, J., (2022) Prototyping crop traits retrieval models for CHIME: dimensionality reduction strategies applied to PRISMA data. Remote Sens 14:2448. https://doi.org/10.3390/rs14102448
139. Poorter H, Niinemets P, L., Wright, I.J., Villar, R., (2009) Causes and consequences of variation in leaf mass per area (lma): a meta-analysis. New Phytol 182:565–588. https://doi.org/10.1111/j.1469-8137.2009.02830.x
140. Radeloff VC, Roy DP, Wulder MA, Anderson M, Cook B, Crawford CJ, Friedl M, Gao F, Gorelick N, Hansen M, Healey S, Hostert P, Hulley G, Huntington JL, Johnson DM, Neigh C, Lyapustin A, Lymburner L, Pahlevan N, Pekel JF, Scambos TA, Schaaf C, Strobl P, Woodcock CE, Zhang HK, Zhu Z (2024) Need and vision for global mediumresolution Landsat and Sentinel-2 data products. Remote Sens Environ 300:113918. https://doi.org/10.1016/j.rse.2023.113918
141. Ranghetti M, Boschetti M, Ranghetti L, Tagliabue G, Panigada C, Gianinetto M, Verrelst J, Candiani G (2023) Assessment of maize nitrogen uptake from PRISMA hyperspectral data through hybrid modelling. Eur J Remote Sens. https://doi.org/10.1080/22797254.2022.2117650
142. Rao P, Zhou W, Bhattarai N, Srivastava AK, Singh B, Poonia S, Lobell DB, Jain M (2021) Using Sentinel-1, Sentinel-2, and Planet Imagery to map crop type of smallholder farms. Remote Sens 13:1870. https://doi.org/10.3390/rs13101870
143. Houborg R, Martha Anderson CD (2009) Utility of an image-based canopy reflectance modeling tool for remote estimation of lai and leaf chlorophyll content at the field scale. Remote Sens Environ 113:259–274. https://doi.org/10.1016/j.rse.2008.09.014
144. Houborg R, Martha Anderson CD (2020) Mapping within-field leaf chlorophyll content in agricultural crops for nitrogen management using Landsat-8 imagery. Precision Agric 21:856–880. https://doi.org/10.1007/s11119-019-09698-y
145. Rast, M., Adams, J., G.F., Nieke, J., Ananasso, C., Bach, H., Ben Dor, E., Chabrillat, S., Colombo, R., Feret, J., Giardino, C., Green, R., Guanter, L., Marsh, S., Ong, C., Rum, G., Schaepman, M., Schlerf, M., Schodlok, M., Skidmore, A., Storch, T., Strobl, P., Williams, M., 2021. Copernicus Hyperspectral Imaging Mission for the Environment - Mission Requirements Document. Scientific report Ref ESA-EOPSM-CHIM-MRD-3216. European Space Research and Technology Centre, Keplerlaan 1 2201 AZ Noordwijk, The Netherlands.
146. Rautiainen M, Hovi A, Schraik D, Hanus J, Lukes P, Lhotakova Z, Homolová L (2024) A spectral–structural characterization of European temperate, hemiboreal, and boreal forests. Earth Syst Sci Data 16:5069–5087. https://doi.org/10.5194/essd-16-5069-2024
147. Reich PB, Walters MB, Ellsworth DS (1997) From tropics to tundra: global convergence in plant functioning. Proc Natl Acad Sci U S A 94:13730–13734. https://doi.org/10.1073/pnas.94.25.13730
148. Reid, W.V., 2005. Millennium Ecosystem Assessment: Ecosystems and Human Well-being. URL: https://www.wri.org/research/millennium-ecosystem-assessment-ecosystems-and-human-well-being [Online; accessed 17. Dec. 2025].
149. Richter R, Hutengs C, Wirth C, Bannehr L, Vohland M (2021) Detecting Tree Species Effects on Forest Canopy Temperatures with Thermal Remote Sensing: the role of spatial resolution. Remote Sens 13:135. https://doi.org/10.3390/rs13010135

150. Roberts DA, Gardner M, Church R, Ustin S, Scheer G, Green RO (1998) Mapping chaparral in the Santa Monica Mountains using multiple endmember spectral mixture models. Remote Sens Environ 65:267–279
151. Rossi C, Kneubühler M, Schütz M, Schaepman ME, Haller RM, Risch AC (2020) From local to regional: functional diversity in differently managed alpine grasslands. Remote Sens Environ 236:111415. https://doi.org/10.1016/j.rse.2019.111415
152. Rukhovich D, Koroleva P, Rukhovich A, Komissarov M (2024) A detailed mapping of soil organic matter content in arable land based on the multitemporal soil line coefficients and neural network filtering of big remote sensing data. Geoderma 447:116941. https://doi.org/10.1016/j.geoderma.2024.116941
153. Schiavon E, Taramelli A, Tornato A, Lee CM, Luvall JC, Uz SS, Townsend PA, Cima V, Geraldini S, Xuan AN, Valentini E, Miller CE (2023) Maximizing societal benefit across multiple hyperspectral Earth observation missions: a user needs approach. J Geophys Res Biogeosciences 128:e2023JG007569. https://doi.org/10.1029/2023JG007569
154. Schlerf M, Atzberger C, Hill J, Buddenbaum H, Werner W, Schueler G (2010) Retrieval of chlorophyll and nitrogen in Norway spruce (*Picea abies* L. Karst.) using imaging spectroscopy. Int J Appl Earth Obs Geoinf 12:17–26. https://doi.org/10.1016/j.jag.2009.08.006
155. Schulz C, Förster M, Vulova SV, Rocha AD, Kleinschmit B (2024) Spectral-temporal traits in Sentinel-1 C-band SAR and Sentinel-2 multispectral remote sensing time series for 61 tree species in Central Europe. Remote Sens Environ 307:114162. https://doi.org/10.1016/j.rse.2024.114162
156. Serbin SP, Wu J, Ely KS, Kruger EL, Townsend PA, Meng R, Wolfe BT, Chlus A, Wang Z, Rogers A (2019) From the Arctic to the tropics: multibiome prediction of leaf mass per area using leaf reflectance. New Phytol 224:1557–1568. https://doi.org/10.1111/nph.16123
157. Simis SGH, Ruiz-Verdu A, Domınguez-Gomez JA, Pena-Martinez R, Peters SWM, Gons HJ (2007) Influence of phytoplankton pigment composition on remote sensing of cyanobacterial biomass. Remote Sens Environ 106:414–427. https://doi.org/10.1016/j.rse.2006.09.008
158. Tagliabue G, Boschetti M, Bramati G, Candiani G, Colombo R, Nutini F, Pompilio L, Rivera-Caicedo JP, Rossi M, Rossini M, Verrelst J, Panigada C (2022) Hybrid retrieval of crop traits from multi-temporal PRISMA hyperspectral imagery. ISPRS J Photogramm Remote Sens 187:362–377. https://doi.org/10.1016/j.isprsjprs.2022.03.014
159. Tranvik LJ, Downing JA, Cotner JB, Loiselle SA, Striegl RG, Ballatore TJ, Dillon P, Finlay K, Fortino K, Knoll LB, Kortelainen PL, Kutser T, Larsen S, Laurion I, Leech DM, McCallister SL, McKnight DM, Melack JM, Overholt E, Porter JA, Prairie Y, Renwick WH, Roland F, Sherman BS, Schindler DW, Sobek S, Tremblay A, Vanni MJ, Verschoor AM, Von Wachenfeldt E, Weyhenmeyer GA (2009) Lakes and reservoirs as regulators of carbon cycling and climate. Limnol Oceanogr 54:2298–2314. https://doi.org/10.4319/lo.2009.54.6_part_2.2298
160. Tucker CJ (1977) Asymptotic nature of grass canopy spectral reflectance. Appl Opt 16:1151–1156. https://doi.org/10.1364/AO.16.001151
161. Tziolas N, Tsakiridis N, Heiden U, van Wesemael B (2024) Soil organic carbon mapping utilizing convolutional neural networks and earth observation data, a case study in Bavaria state Germany. Geoderma 444:116867. https://doi.org/10.1016/j.geoderma.2024.116867
162 Ustin SL, Middleton EM (2021) Current and near-term advances in Earth observation for ecological applications. Ecol Proc. https://doi.org/10.1186/s13717-020-00255-4
163. Vela Almeida D, Kolinjivadi V, Ferrando T, Roy B, Herrera H, Vecchione Gonçalves M, Van Hecken G (2023) The "Greening" of Empire: the European Green Deal as the EU first agenda. Polit Geogr 105:102925. https://doi.org/10.1016/j.polgeo.2023.102925
164. Verrelst J, Halabuk A, Atzberger C, Hank T, Steinhauser S, Berger K (2023) A comprehensive survey on quantifying non-photosynthetic vegetation cover and biomass from imaging spectroscopy. Ecol Indic 155:110911. https://doi.org/10.1016/j.ecolind.2023.110911
165 Verrelst J, Malenovsky Z, Tol C, Camps-Valls G, Moreno J (2019) Quantifying vegetation biophysical variables from imaging spectroscopy data: a review on retrieval methods. Surveys Geophys. https://doi.org/10.1007/s10712-018-9478-y
166. Verrelst J, Rivera-Caicedo JP, Reyes-Munoz P, Morata M, Amin E, Tagliabue G, Panigada C, Hank T, Berger K (2021) Mapping landscape canopy nitrogen content from space using PRISMA data. ISPRS J Photogramm Remote Sens 178:382–395. https://doi.org/10.1016/j.isprsjprs.2021.06.017
167. Vertucci FA, Likens GE (1989) Spectral reflectance and water quality of Adirondack mountain region lakes. Limnol Oceanogr 34:1656–1672. https://doi.org/10.4319/lo.1989.34.8.1656
168. van Vliet J (2019) Direct and indirect loss of natural area from urban expansion. Nat Sustain 2:755–763. https://doi.org/10.1038/s41893-019-0340-0
169. Ward KJ, Foerster S, Chabrillat S (2024) Estimating soil organic carbon using multitemporal PRISMA imaging spectroscopy data. Geoderma 450:117025. https://doi.org/10.1016/j.geoderma.2024.117025
170. van Wesemael B, Abdelbaki A, Ben-Dor E, Chabrillat S, D'Angelo P, Dematte JAM, Genova G, Gholizadeh A, Heiden U, Karlshoefer P, Milewski R, Poggio L, Sabetizade M, Sanz A, Schwind P, Tsakiridis NL, Tziolas N, Yague J, Zízala D (2024) A European soil organic carbon monitoring system leveraging sentinel 2 imagery and the Lucas soil data base. Geoderma. https://doi.org/10.2139/ssrn.4903501
171. Wegler M, Kacic P, Thonfeld F, Holzwarth S, Jaggy N, Gessner U, Kuenzer C (2025) Tree species from space: a new product for Germany based on Sentinel-1 and -2 time series. Int J Remote Sens 46:6075–6108. https://doi.org/10.1080/01431161.2025.2530236
172. Wetzel, R.G. (2001) Limnology: Lake and River Ecosystems. Academic Press Elsevier, San Diego. https://www.sciencedirect.com/book/monograph/9780127447605/limnology
173. Wocher M, Berger K, Danner M, Mauser W, Hank T (2018) Physically-based retrieval of canopy equivalent water thickness using hyperspectral data. Remote Sens 10:1924. https://doi.org/10.3390/rs10121924
174. Wright IJ, Reich PB, Westoby M, Ackerly DD, Baruch Z, Bongers F, Cavender-Bares J, Chapin T, Cornelissen JHC, Diemer M, Flexas J, Garnier E, Groom PK, Gulias J, Hikosaka K, Lamont BB, Lee T, Lee W, Lusk C, Midgley JJ, Navas ML, Niinemets O, J., Osada, N., Poorter, H., Poot, P., Prior, L., Pyankov, V.I., Roumet, C., Thomas, S.C., Tjoelker, M.G., Veneklaas, E.J., Villar, R., (2004) The worldwide leaf economics spectrum. Nature 428:821–827. https://doi.org/10.1038/nature02403
175. Xi H, Hieronymi M, Röttgers R, Krasemann H, Qiu Z (2015) Hyperspectral differentiation of phytoplankton taxonomic groups: a comparison between using remote sensing reflectance and absorption spectra. Remote Sens 2015(11):14781–14805. https://doi.org/10.3390/rs71114781
176. Yebra M, Dennison PE, Chuvieco E, Riano D, Zylstra P, Hunt ER, Danson FM, Qi Y, Jurdao S (2013) A global review of remote sensing of live fuel moisture content for fire danger assessment: moving towards operational products. Remote Sens Environ 136:455–468. https://doi.org/10.1016/j.rse.2013.05.029
177. Yebra M, Scortechini G, Adeline K, Aktepe N, Almoustafa T, Bar-Massada A, Beget ME, Boer M, Bradstock R, Brown T, Castro FX, Chen R, Chuvieco E, Danson M, Degirmenci CU, Delgado-Dávila R, Dennison P, Di Bella C, Domenech O, Féret JB, Forsyth G, Gabriel E, Gagkas Z, Gharbi F, Granda E, Griebel A, He B, Jolly M, Kotzur I, Kraaij T, Kristina A, Kütküt P, Limousin JM, Martin MP, Monteiro AT, Morais M, Moreira B, Mouillot F, Msweli S, Nolan RH, Pellizzaro G, Qi Y, Quan X, Resco de Dios V, Roberts D, Tav¸sano˘glu, C¸., Taylor, A.F.S., Taylor, J., Tüfekcioglu, I., Ventura, A., Younes Cardenas, N., (2024) Globe-LFMC 2.0, an enhanced and updated dataset for live fuel moisture content research. Sci Data 11:1–12. https://doi.org/10.1038/s41597-024-03159-6
178. Zarco-Tejada PJ, Miller JR, Mohammed G, Noland TL, Sampson P (2002) Vegetation stress detection through chlorophyll a+ b estimation and fluorescence effects on hyperspectral imagery. J Environ Qual 31:1433–1441. https://doi.org/10.2134/jeq2002.1433

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