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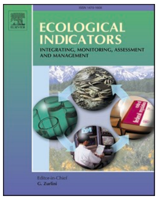

Review

Review of remote Sensing indices for monitoring environmental grassland indicators in Europe

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ABSTRACT

European grasslands provide biodiversity, carbon storage, and agricultural services, but face increasing pressure from intensification and climate change. We review remote sensing indices used to monitor conservation-relevant grassland environmental indicators in Europe, covering biochemical, structural, spatial, and temporal indices from satellite, airborne, uncrewed aerial vehicle (UAV) and ground-based sensors. We synthesize best-practice applications for landscape/habitat/species identification, biomass and LAI, biodiversity, management, fluxes, and temporal dynamics, and summarize key limitations (e.g., saturation and background effects, mixed pixels, and limited model transferability). Finally, we outline how data fusion and emerging hyperspectral/thermal missions can improve operational, policy-ready monitoring.

1. Introduction

Grasslands are the dominant terrestrial land cover and cover of EU agricultural land (Eurostat, 2020) European grasslands – including Iberian tree-grass ecosystems like *Dehesas* and *Montados* – support high biodiversity and key ecosystem services (García-Feced et al., 2015). They are shaped by climate/ soil variability, and management intensities. Yet, permanent grasslands are under pressure from land-use conversion, intensification, shrub encroachment, and climate warming. Although plowing typically requires permits in Europe, intensified use (e.g., fertilization, sowing productive species) threatens extensive grassland, while abandonment drives succession. Still grasslands have lower conservation priority than forests, contributing to higher loss rates (Pillar and Overbeck, 2025).

Environmental indicators are quantifiable variables describing ecosystem state, pressures, or responses. By condensing complex information, they support conservation and policy needs (e.g., biodiversity condition, Grassland Use Intensity (GLUI), habitat quality) (Elmiger et al., 2023) and are applied in for example conservation-status assessments under the Habitats Directive.

Remote sensing (RS) extends observation beyond-visible spectra (near-infrared (NIR), thermal infrared (TIR), microwave), improving environmental characterization (Khorram et al., 2012). RS indices are calculated proxies derived from one or more sensor-based variables to simplify, summarize, or highlight biochemical, structural, spatial, or temporal characteristics. For example, the biochemical index Normalized Difference Vegetation Index (NDVI, red/NIR) serves as a proxy for green biomass (Rouse et al., 1974). See table 2 in the supplementary material for all formulas, sensitivity, robustness/confounders, typical applicability and origin source of biochemical RS indices mentioned in this review. Synthetic Aperture Radar (SAR) and Light Detection and Ranging (LiDAR)-based indices support assessment of vegetation

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structure and mowing events. Indices can be mapped across space and time to detect spatial patterns and trends. In this review, we use environmental *indicators* for the ecological property to be assessed and RS *indices* for the RS metric used to estimate that property. Indices act as proxies that require appropriate calibration and validation against field data. Because field monitoring is costly and labor-intensive, RS enables spatially and temporally continuous monitoring and can be cost-effective given open satellite archives and declining UAV costs.

Increasing interest in grasslands RS, resulted in numerous published reviews (research trends (Pinna et al., 2024), UAVs (Lyu et al., 2022), hyperspectral (van Cleemput et al., 2018), management (Reinermann et al., 2020), grassland health (Soubry et al., 2021), ecosystem services (Masenyama et al., 2022), phenology (Matongera et al., 2021), or bush encroachment (Soubry and Guo, 2022). Meanwhile, Wang et al. (2022) examined parameters such as biomass, productivity, fractional vegetation cover, and leaf area index (LAI), alongside specific applications, including degradation, grassland use, disaster, and carbon cycle monitoring.

A consolidated Europe-focused synthesis of conservation-relevant grassland indicators explicitly centered on RS indices remains novel. We therefore focus on European grasslands—shaped by a long agricultural history and aligned with EU policy priorities—to summarize indices commonly used to derive conservation-relevant indicators and to synthesize best practices, challenges, and mitigation strategies. Specifically, we:

- review key RS indices for grassland monitoring for species, habitat and landscape identification, biodiversity, biomass, fluxes and temporal dynamics including ecological processes and management;
- compile best practice monitoring applications and underlying principles;
- identify challenges, demands, and limitations and propose strategies to improve accuracy, efficiency, and reliability.

2. Method

We conducted a systematic literature *Web of Science* search. For the full review, we retrieved peer-reviewed articles and reviews on RS and grassland published 2012–2023 using an expanded keyword set; search terms and synonyms are provided in full in the supplementary material. Relevant papers from 2024 to 2025 were added subsequently but excluded from the main analysis.

We screened records using the following constraints (applied manually and/or via negative search terms):

2.1. Study region

We focus on European grasslands within the Alpine, Atlantic, Boreal, Continental, and Mediterranean biogeographic regions. We excluded atypical/limited-extent regions (Arctic, Pannonian and Steppic regions; Black Sea; Macaronesia) due to substantially different conditions and limited comparability.

2.2. Grasslands

We include managed, semi-natural and permanent natural grasslands, including multifunctional tree-grass systems (EU Habitat Directive habitat codes 6xxx / EUNIS E). Following Habitats Directive/EUNIS separations, we exclude heath and scrublands (4xxx / EUNIS F) and peatland systems (7xxx / EUNIS D).

2.3. Topics

We structured the review into six topics that cover conservation and policy (e.g., agri-environmental schemes and Habitats Directive) relevant, remotely observable and transferable indicator families that are dominantly studied in Europe, maximizing coverage while avoiding fragmentation into narrowly scoped topics:

1. **Identification**: habitat/landscape mapping and discrimination (grassland vs crops/shrubs; habitat classes), a foundation for conservation planning, and change detection.
2. **Plant traits:** biomass and LAI as productivity/management proxies relevant for carbon cycling, habitat quality, and management intensity
3. **Biodiversity:** plant diversity as an ecological state variable
4. **Fluxes:** Evapotranspiration (ET) and Gross Primary Production (GPP) as ecosystem-function and productivity dynamic indicators central to climate adaptation
5. **Long-term temporal dynamics**: phenology, degradation, and recovery, trends/anomalies from time series to capture processes and resilience
6. **Management/short-term temporal dynamics:** mowing, grazing, and fire are decisive drivers of habitat condition and compliance.

Our topic scan intentionally excludes themes that lie outside environmental-indicator monitoring, are production-centric, or are not core targets of European conservation policy reporting (e.g. soil quality, soil moisture, yield, plant traits linked to nutrient status or forage quality). See the Supplementary Data for detailed selection.

3. Results

European grassland-monitoring research varied strongly across countries and biogeographical regions (Fig. 1). From 2012 to 2024, the share of grassland-related RS studies increased steadily (Fig. 2a; see also Supplementary Fig. S-1 for device and satellite trends). Dominant topics were mapping plant traits (biomass, LAI), management, and species/habitat identification (Fig. 2b). Spatial and temporal scales of the studies were depending on the environmental indicator examined (Fig. 3).

We grouped RS indices that reduce data complexity, improve key information, or represent temporal or spatial behaviors into four classes (see also Supplementary Fig. S-3 for classification):

(1) **biochemical indices** (including *vegetation indices (VIs)* combining two or more spectral bands; (2) **structural indices** from SAR, LiDAR, or optical data, including Radar Vegetation Indices (RVI) and polarimetric SAR (PolSAR) parameters, often used for mowing detection or biomass estimation; (3) **temporal indices** summarizing time series or phenology metrics, including coherence from InSAR, a bitemporal measure (Supplementary Fig. S-4); and (4) **spatial indices** capturing spectral or textural patterns, from object-level statistics to GLCM metrics.

3.1. Identification - from species to landscape

At the land cover level, grassland discrimination targets separation of grasslands from non-grassland (d'Andrimont et al., 2018), distinction from other crops (Dusseux et al., 2014), separation from shrublands (Bayle et al., 2019), and identification of biotopes, habitats, and high nature value (HNV) grasslands (Stenzel et al., 2017). Tree and shrub cover are key indicators for monitoring grassland succession (Kupidura et al., 2019). Identifying the status quo supports environmental planning, protected area designation, and attributation of change to climate or land use.

RS identification assumes that species, habitats, biotopes, or vegetation classes possess detectable spectral, temporal, or structural signatures. Spectral “fingerprints” reflect wavelength-dependent reflectance/absorption patterns influenced by pigments, leaf structure, canopy density, and plant morphology, while structural fingerprints capture arrangement- and density-driven texture/roughness effects.

Species mapping is constrained by small individual size relative to typical sensor resolution; thus, most studies target habitat types or

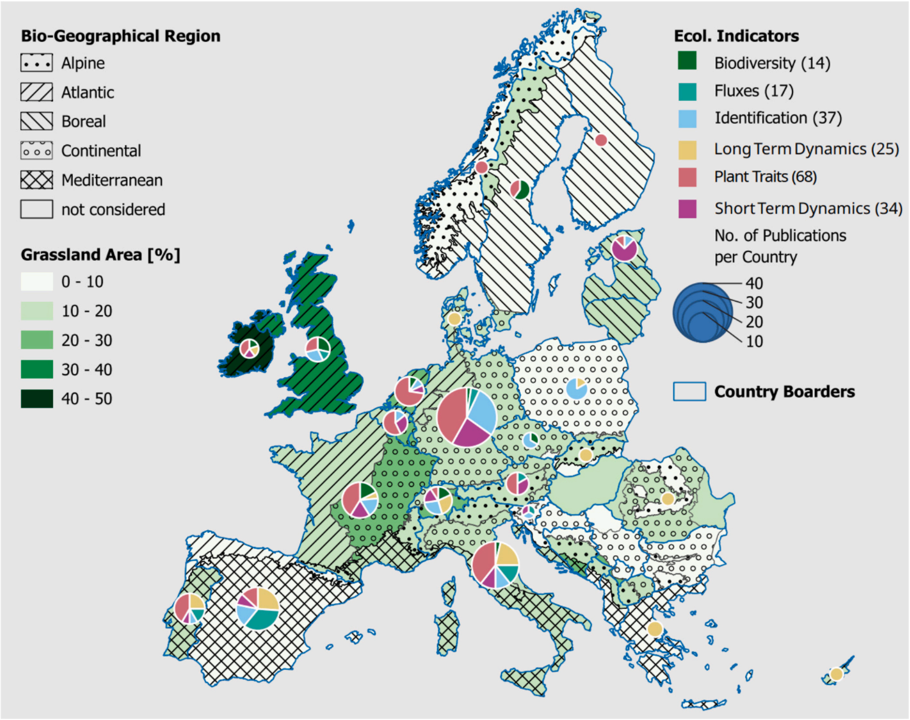
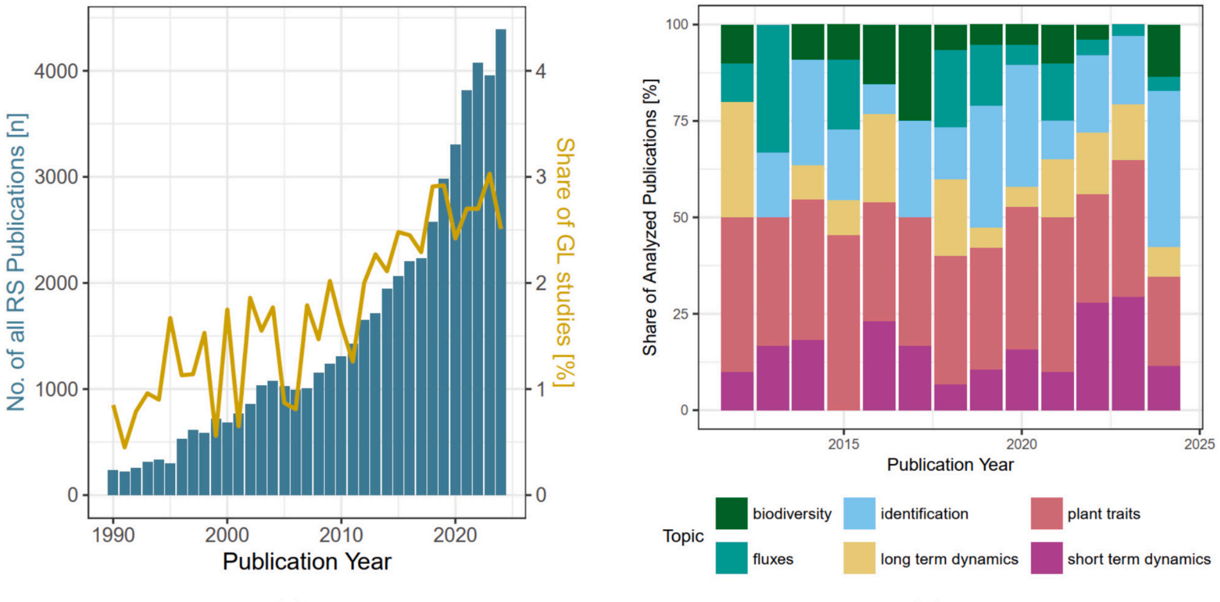


Fig. 1. Studied countries and biogeographical regions with number of publications per country (pie chart), per region and ecological indicator (in brackets). The Grassland area share by country and bio- geographical region was derived from the High Resolution Layer Grassland 2018 with 100 m resolution (European Environment Agency, 2020).



(a) (b)

Fig. 2. Research interest in grassland monitoring studies with RS. In (a) the proportionate research output from grassland monitoring studies with remote sensing in relation to all RS studies from 1990 to 2023 is shown. (b) shows the studies analyzed in this review from 2012 to 2024 proportionate by ecological indicator by year.

optically distinctive features (e.g. flowers or phenology). Indirect approaches embed RS predictors into species distribution models (Pottier et al., 2014), leveraging environmental information in the signal. At landscape, habitat, or biotope scales, spatial resolution is less limiting though higher resolution better captures small-scale heterogeneity.

In vegetation vs. non-vegetation classification dry or senescent vegetation can resemle bare soil. RE indices (e.g. RE Chlorophyll Index) improved grassland vegetation cover estimation relevant to degradation (Andreatta et al., 2022). For sparse cover over bright backgrounds, spectral unmixing can outperform indices (Frantz et al., 2022) and unmix photosynthetic vegetation (PV), non-photosynthetic vegetation (NPV), and soil (Kowalski et al., 2022). However, robust end-member definitions remains critical and may limit transferability to heterogeneous landscapes (Lewińska et al., 2025).

Permanent grasslands and crops can be differentiated via exposed soil, characteristic in crop rotations. Vegetation-soil contrast is strongest

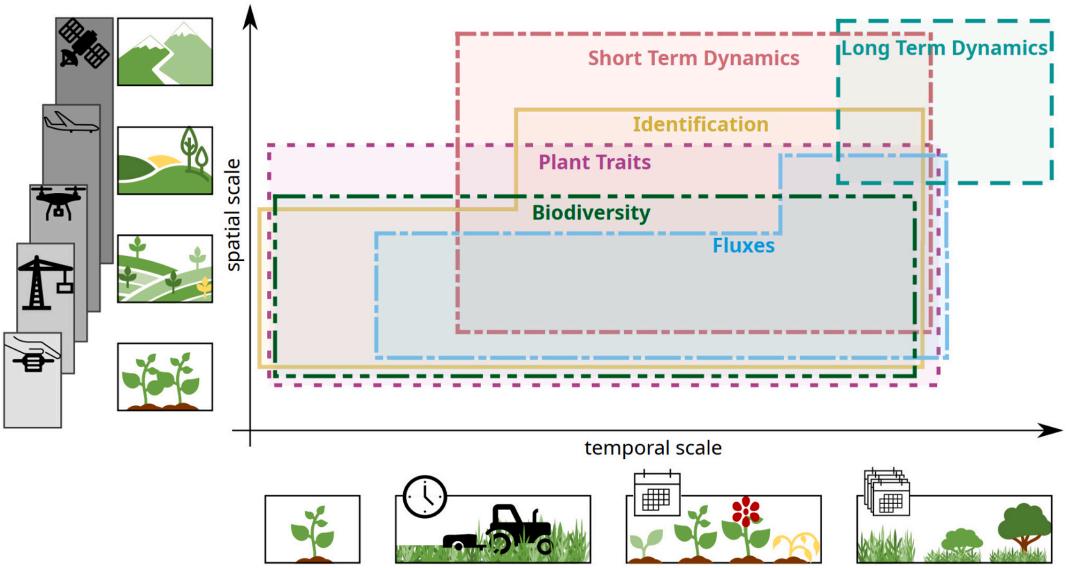


Fig. 3. Spatial-temporal scale of RS studies for environmental indicators. The temporal scale ranges from mono-temporal to decades, and the spatial scale ranges from single species to landscapes.

in VNIR. The Bare Soil Index can separate bare soil from grasslands, but may confuse open soil with heavily grazed meadows (d'Andrimont et al., 2018). Temporal indices (e.g., harmonic metrics) combined with textural and topographic metrics can improve classification by capturing phenology and terrain effects (Vannoppen et al., 2023).

Shrublands differ from grasslands through higher biomass and distinct structure. Indices such as the Normalized Anthocyanin Reflectance Index (NARI), texture metrics and the blue band can support mapping of tree and shrub distribution (Bayle et al., 2019; Kupidura et al., 2019; Fragoso-Campón et al., 2020).

Across habitat mapping structural similarity can yield comparable spectra, but traits and temporal dynamics improve discrimination: In Switzerland, NDVI/NDWI, NIR/SWIR bands, and seasonal temporal indices were influential (Huber et al., 2023). HNV grassland identification was driven by seasonal temporal indices, RE, and spectral change features (Gröschler et al., 2025). Hyperspectral data can provide additional gains for mountain habitat classification compared to multispectral or SAR data (Patriarca et al., 2025).

3.2. Biomass and leaf area index

LAI and biomass are related to plant growth. LAI is directly linked to photosynthetic capacity (Watson, 1947). RS measures above-ground biomass and may distinguish photosynthetic active (green) biomass from senescent biomass. Biomass and LAI are central to ecosystem energy flows and carbon cycling and support assessments of land-use change and management practices.

Biomass retrieval via RS commonly assumes that increasing biomass amplifies vegetation spectral effects: higher NIR reflectance and stronger red absorption and thus increasing NDVI. Biomass-driven structural changes affect SAR volume scattering: increased volume scattering reduces radiation reflected back to the sensor.

For LAI assessment, studies used VIs, spectral bands, and radiative transfer models (RTM). RE-based indices were promising (Imran et al., 2020), while NDVI was more sensitive to saturation effects (Asam et al., 2013). RTM-based applications applied the PROSAIL model, enabling simulated LAI to be compared with field measurements or used as biomass proxies (Klingler et al., 2020*)*. Schwieder et al. (2020) compared an empirical random forest model with an RTM and identified the RE-NIR region as most important for both LAI and biomass.

Optical indices dominated biomass retrieval and NDVI was most common, however, alternative optical indices often outperformed NDVI (Barrachina et al., 2015; Grüner et al., 2020; Dusseux et al., 2022). Green and RE bands emerged as promising alternatives (Chiarito et al., 2021); indices such as Renormalized Difference Vegetation Index (RDVI), Modified Soil Adjusted Vegetation Index (MSAVI), and Optimized Soil Adjusted Vegetation Index (OSAVI; Jenal et al., 2020) have been shown to be more suitable although performance is context-dependent (grassland types, seasons), so rankings should not be generalized to a single 'best' index. In direct comparison, NDVI outperformed backscatter (Hajj et al., 2014).

Textural indices (e.g. Haralick feature) have improved biomass estimates (Grüner et al., 2020), and combining hyperspectral and SAR data further enhanced performance (Chiarito et al., 2021).

3.3. Biodiversity

Biodiversity spans genetic to ecosystem levels and varies across spatial and temporal scales. Standard biodiversity data collection is conducted in-situ, documenting species distributions and population characteristics, yet monitoring often relies on simple indicators (e.g., vascular plants richness) and expert judgement. This section focuses on plant diversity, commonly described as taxonomic, functional, and phylogenetic diversity. Taxonomic indices (e.g., richness, evenness, Simpson, Shannon) from botanical surveys elucidate species composition; functional diversity captures trait differences relevant to ecosystem functioning; phylogenetic diversity quantifies evolutionary relationships.

RS of grassland plant diversity follows two main approaches: (i) indirect inference via habitat mapping using fine-to-moderate spatial/spectral resolution data (Rocchini et al., 2007), and (ii) direct approaches targeting functional types or spectral diversity, usually requiring finer spatial and spectral resolutions (Wang and Gamon, 2019). Direct species mapping remains uncommon in grasslands because individuals are small (see Section 4.1).

Indirect approaches relate RS environmental predictors to biodiversity variables, drawing on theory linking diversity to climatic stability, productivity, and habitat structure (MacArthur, 1984). Habitat heterogeneity metrics (e.g. Haralick metrics; Haralick et al., 1973) have been used as proxies and airborne hyperspectral data has renewed interest in the spectral variation hypothesis (SVH), which links higher spectral variation to greater plant diversity (Palmer et al., 2002).

Studies using fine spectral resolution emphasize pigment-sensitive VIS and structure-sensitive NIR regions (Möckel et al., 2016a). However, optimal bands vary across functional groups, limiting generalization. Medium spatial resolution spectral-diversity studies are comparatively rare (e.g., Schmidtlein and Fassnacht, 2017), and spatial resolution is often the main constraint for relating spectral- to functional diversity (Pacheco-Labrador et al., 2022). Matching sensor resolution to target size may require sub-centimeter detail (Lopatin et al., 2017). Accordingly, medium resolution may be inadequate for direct estimation and is better suited to indirect inference via habitat variation.

3.4. Carbon and water fluxes

Grassland – particularly in semi-arid regions – are important components of global biogeochemical cycles (Ahlström et al., 2015). Water and carbon fluxes key targets for RS-based monitoring.ET, is a primary drought indicator in grasslands and links water balance, carbon and energy cycles. ET is highly dynamic and controlled by soil–vegetation–atmosphere interactions with strong phenological seasonality. RS provides the most feasible approach to estimate ET at different spatio-temporal scales. Methodically, ET is commonly retrieved using TIR-based surface energy balance models (SEB) models – including two-source formulations (TSEB) (Andreu et al., 2018; Burchard-Levine et al., 2021, 2022; González-Dugo et al., 2021) or estimated by scaling reference ET with NDVI-based coefficients within precipitation-driven soil water balance models (Carpintero et al., 2020).

In drought applications, ET products are frequently complemented by vegetation moisture and stress proxies from optical indices and SAR backscatter, which can increase sensitivity to short-term water limitation (e.g., Wang et al., 2022; Bernardino et al., 2024).

GPP is a key component of the global carbon cycle is widely estimated from RS using optical data within light-use efficiency concepts. NDVI remains common via its relationship to fAPAR (Fensholt et al., 2004), but saturation motivates alternative VIs (Barrachina et al., 2015). The photochemical Reflectance Index (PRI) has been frequently adopted as a proxy for light-use efficiency, yet it is sensitive to phenology, leaf age, or environmental conditions (Perez-Priego et al., 2015). Studies therefore emphasize combining complementary spectral information, including solar-induced fluorescence (SIF) and pigment/water/senescence-related indices, to improve GPP estimates across phenological stages and management conditions (Perez-Priego et al., 2015; Sakowska et al., 2019).

Multi-site analyses further suggest that visible-band and multi-band combinations can outperform NIR-only indices where canopy-structure differences confound simple correlations (Balzarolo et al., 2015).

3.5. Temporal dynamics

Grassland temporal dynamics comprise abrupt disturbances (e.g. fires, management), gradual trends (e.g. bush encroachment), and recurring seasonal processes such as phenology. Characterizing change requires considering its rate and separating trend, disturbance, and seasonal components, which are shaped by long-term climate, short-term weather and extremes, and land-use change. Consequently, temporal grassland analyses rely on time-series observations within and across years, as change is only detectable relative to the temporal trajectory.

3.5.1. Seasonal and long term temporal dynamics

Plant phenology (morphological development) can be monitored through repeated observations during the growth cycle; detailed, species-specific stages are commonly recorded in fieldwork using schemes, but this is time-consuming and requires expert knowledge. In grasslands, phenology is central for assessing ecosystem services and large-scale vegetation dynamics (development/vigor, resilience, and compositional change). Key phases in grassland RS are start of season (SOS), peak productivity (day of peak, DOP), and end of season (EOS). Phenological change is an important indicator of global warming with evidence for earlier SOS and altitudinal shifts in European grasslands (Bellini et al., 2023). SOS detection is challenging due to gradual greening; integrating MODIS NDVI with weather data improved SOS estimation in Austria (Dujakovic et al., 2024).

Here, *ecological processes* refer to long-term observations of grassland habitats (e.g. structural change, post-fires recovery, degradation and shrub encroachment (Bayle et al., 2019), resilience to overgrazing (von Keyserlingk et al., 2021), or drought (Kowalski et al., 2024; Kowalski et al., 2022). These analysis support applied conservation (e.g., NATURA 2000), monitoring of conservation status (Corbane et al., 2015), ecosystem stability (White et al., 2022), and habitat-quality assessment (Schmidt et al., 2017). In Europe, studies are concentrated in climatically marginal regions such as the Mediterranean and Alpine grasslands.

Sensor choice reflects space–time requirements. For long-term processes, studies prioritize stable, long-running archives, especially MODIS (White et al., 2022) and Landsat (Suess et al., 2018) where time-series continuity often outweighs spatial detail and even one to few observations per year can reveal trends. Lower temporal resolution hyperspectral data could add value via richer spectral and textural information for shrub height or biomass monitoring (Ningthoujam et al., 2025).

Grassland phenology is usually derived from time series using VIS-NIR contrast indices, especially NDVI, with phenophases often detected via absolute or relative thresholds (Jönsson and Eklundh, 2004). Proximal, narrow-band sensors can continuously monitor small fractions and enable indices targeting photosynthetic regulation or chlorophyll dynamics (e.g. PRI or Canopy Chlorophyll Content Index (CCCI)), but measurements show high spatio-temporal variability and a strong influence of NPV (Porterie et al., 2025). Phenocams can offer high-frequency observations where Green Chromatic Coordinate (GCC) is effective for phenophase detection (Cremonese et al., 2017). Multi-sensor fusion can densify time series but introduces compatibility challenges. SAR - often alongside optical data – has been used via backscatter (Stendardi et al., 2019), coherence (Löw et al., 2024), and polarization indices (e.g. RVI, Holtgrave et al., 2020) and is becoming increasingly relevant for grasslands.

3.5.2. Management and short-term temporal dynamics

Abrupt temporal changes in grasslands include disturbances such as fires or management. RS-based fire studies focused mainly on Mediterranean regions and typically aim to map fire-prone areas, quantify burn severity, or monitor post-fire recovery (e.g. Fernández-García et al., 2018). Grassland management significantly impacts ecological processes and landscape structure, yet monitoring is challenging because management signals can be subtle and gradual compared with logging or crop harvest.

Because management monitoring requires high temporal resolution, radar-based structural indices were widely used, particularly for mowing detection via abrupt structural changes (e.g., Voormansik et al., 2016). Optical biochemical indices are often combined with radar structural indices to mitigate gaps in optical time series (Reinermann et al., 2022; Holtgrave et al., 2023). Beyond event detection, Potočnik Buhvald et al. (2022) classified extensively versus intensively managed grasslands using smoothed time series, finding highest accuracy from combining NDVI, SAR coherence and topographic information. For long-term trends, a key challenge is separating short-term management effects from underlying trends and disruptions possible with e.g., BFAST (Verbesselt et al., 2010).

In fire studies, NDVI was frequently applied, especially for post-fire monitoring (Vinué-Visús et al., 2022), whereas Relative Burned Ratio (RBR) and the Normalized Burn Ratio (NBR) have shown strong performance for identifying fire-prone areas (de Simone et al., 2020; García-Llamas et al., 2019). Trend analyses historically relied on NDVI or

EVI (White et al., 2022) but additional indices, such as NARI or normalized difference fraction index (NDFI) derived from spectral unmixing, were introduced (Bayle et al., 2019; Kowalski et al., 2022).

4. Discussion

This review identifies the most effective RS indices to monitor grassland environmental indicators, synthesizes key limitations and practical mitigation options (see table 1).

The share of grassland monitoring within RS research increased from ~1% (1990s) to ~2.5% (2025) (see Fig. 2a), coinciding with greater data availability (e.g., Sentinel since 2014), opened archives (e.g. Landsat, Wulder et al., 2012), and cloud platforms (e.g., Google Earth Engine (GEE) or Data and Information Access Services (DIAS) (Gorelick et al., 2017) as well as dedicated toolchains (e.g. Framework for Operational Radiometric Correction for Environmental Monitoring (FORCE) (Frantz, 2019)) together with exponential growth in computational power. In Europe, growth is also driven by conservation and climate-policy demand and funding (e.g., CAP, Biodiversity Strategy 2030, EU Habitat Directive, Horizon 2020, and Horizon Europe; Haensel et al., 2023). Emerging initiatives are likely to sustain this research direction (e.g. HNV farmland, Green Deal, Farm-to-Fork strategy, Nature Restoration Law).

4.1. *Indices, models, and environmental indicators*

4.1.1. *Transferability*

A central limitation of grassland RS is model transferability across regions, grassland types, and time, reflecting strong site dependance of VIs and spectral-biophysical relationships (Wijesingha et al., 2024). Consequently, predictions (e.g., yield, or habitat discrimination) often do not generalize between grassland habitats or sites (Goodsell et al., 2024; Tarantino et al., 2021). Transfer failure is driven by environmental heterogeneity (e.g. canopy structure, nutrient/ soil effects) and variability in radiative or energy-balance terms, so similar biophysical states can produce different spectral responses across landscapes (Pottier et al., 2014; Feng et al., 2015). Also, many nonparametric models cannot extrapolate beyond the feature space represented in training data (Franceschini et al., 2022). Temporal transferability is further constrained by interannual climate variability, which alters grassland properties and reduces model applicability (Shahrokhnia and Ahmadi, 2019; Franceschini et al., 2022), especially relevant because grassland reacts quickly to lack of precipitation (Kowalski et al., 2024),.

Biodiversity mapping is particularly transfer-limited because grasslands span complex ecological gradients that are not present in croplands. The SVH is attractive but sensitive to phenology, spatial resolution, canopy complexity, and environmental gradients, yielding inconsistent results across studies (Fassnacht et al., 2022; Wallis et al., 2024). Normalization can improve generalizability, but robust, universal approaches remain elusive (Pacheco-Labrador et al., 2023). Spectral diversity indices require careful consideration of environmental and management context (Wallis et al., 2025).

Improving transferability will likely require localized or stratified models tailored to grassland types and conditions, broader reference datasets across space and time; multiscale, multimodal modeling integrating spectral, structural, and temporal information (Schweiger et al., 2015). Such strategies are particularly relevant for emerging deep-learning workflows, which may improve transfer under heterogeneous conditions by learning from diverse and irregular time series.

4.1.2. *Index selection*

Current grassland monitoring often underuses the information content of RS data. Many workflows rely on limited samples and single-date features, whereas fuller exploitation of spatiotemporal context (e.g., neighborhood information in space and time) remains comparatively rare. The electromagnetic spectrum is not fully leveraged: SAR is still used in relatively few grassland studies despite its sensitivity to structure, moisture, and roughness (Szigarski et al., 2018), although it is increasingly applied in management monitoring where frequent acquisitions support time-critical mowing detection.

In the optical domain, SWIR and blue bands are often overlooked despite added value for pigments (blue) and vegetation water status (SWIR) (see Supplementary Fig. S-5). Blue-band information can support grass-shrub discrimination (Fragoso-Campón et al., 2020), while SWIR underpins drought and canopy water metrics (e.g. NDWI; Gao, 1996).

A further limitation is index-indicator mismatch. NDVI is affected by saturation at high biomass and soil background (see table 1, supplementary material) and does not explicitly represent NPV or senescent biomass (Butterfield and Malmström, 2009). This is critical in conservation grasslands where NPV can be abundant and spectrally close to soil due to reduced chlorophyll (Pacheco-Labrador et al., 2021). Hyperspectral missions may help by capturing narrow spectral features linked to senescent material, but revisit constraints often require fusion approaches that pair multispectral time series with hyperspectral snapshots.

Vegetation-identification studies report inconsistent performance of common indices (NDVI, GNDVI, SAVI): some find alternative single indices outperform them (Villoslada et al., 2020), others show combinations improve discrimination (Tarantino et al., 2021). In biodiversity applications, NDVI or EVI combined with spectral diversity metrics may miss functional trait variations, and many grassland types remain spectrally similar, limiting separability. Consequently, leveraging multiple bands, and especially hyperspectral data is advantageous.

Overall, the absence of a consistently “best” index across tasks supports context-aware feature design and data-driven ML/DL workflows that ingest multi-band, multi-sensor, multi-temporal inputs rather than relying on preselected indices.

4.1.3. *Selection of environmental indicators*

Many environmental indicators used in on-site monitoring are difficult to estimate with RS. Direct mapping of individual grassland species remains constrained by plant size and sensor resolution and may not be the most practical monitoring target. A more feasible direction are functional traits, which can indicate compositional and ecological change, and may better capture conservation value over time (Thornley et al., 2023). Hyperspectral studies have shown that optical traits can map ecological characteristics such as Ellenberg values (Möckel et al., 2016b). While functional/phylogenetic diversity and turnover (beta diversity) remain underrepresented, research is increasingly moving toward these trait-based perspectives (Rocchini et al., 2018). Finally, involving stakeholders in product development can improve operational relevance by co-designing environmental indicators that are both remotely measurable and policy-aligned (e.g., mowing cycles/dates), supported by authority field data for calibration and validation.

4.2. *Spatial and temporal considerations*

4.2.1. *Spatial Resolution and Heterogeneity*

Spatial resolution must match the target scale (species, plot, habitat, landscape). Species and habitat mapping in heterogeneous grasslands requires high resolution, but remains challenging because individual plants are small relative to most sensors and show high spectral plasticity driven by site conditions (e.g., dryness), increasing misclassification risk. At coarser resolution, mixed pixels are pervasive: grasslands contain many species within small patches (unlike monospecific croplands or forests), with subpixel variation in phenology and leaf traits.

Mixed pixels are particularly problematic in tree-grass mosaics ET uncertainties increases when pixels cannot separate trees from grass (Burchard-Levine et al., 2021). Methodological adaptation include parameter tuning for tree-grass ET (Andreu et al., 2018) and multi-component energy balance formulations (e.g., 3SEB) that explicitly represent trees and grass (Burchard-Levine et al., 2022). High-resolution data (e.g., UAV) offer detail but limited spatial coverage and high operational cost, whereas low-resolution data improve coverage but can miss fine-scale details leading to oversimplified interpretations. This resolution-coverage trade-off requires aligning sensor choice with the application.

4.2.2. *Temporal influences*

A major strengths of RS is its ability for frequent, long-term observation. Studies have combined structural indices from SAR with spectral indices to characterize phenological stages (Dronova and Taddeo, 2022), and Sentinel-1/2 comparison show SAR can help bridge gaps in cloud-limited optical time series across phenological phases (Holtgrave et al., 2020). Standard spectral indices (NDVI, EVI) were used for phenology (Dronova and Taddeo, 2022) and PhenoCams are promising for tracking phenology in tree-grass ecosystems (Luo et al., 2018). However, remotely sensed greenness stages mismatch with ground phenology with differences from days to weeks (Butterfield and Malmström, 2009).

Dense time series are critical for mowing event detection. Optical approaches are limited by cloud cover, while SAR complements improve continuity but can complicate interpretation; recent work evaluated optical-, SAR-, and fused approaches with a focus on transferability (Schwieder et al., 2025). Weather-driven variability further complicate separation of natural dynamics from management effects, and acquisition timing is critical for mowing detection and biomass estimation (Barrachina et al., 2015).

4.3. *External factors and data quality*

4.3.1. *External factors influencing the signal*

Grassland reflectance is a composite of plant components, soil, and litter, plus structural shading, which complicates interpretation. Soil moisture affects both optical and SAR signals: Wet soils absorb more radiation and reduce reflectance and, soil color further modulates the signal. These effects are strongest under sparse cover, more common in grasslands than in forests or crops.

Drought stress alters SWIR (water-content sensitive) and changes VIS-NIR reflectance via chlorophyll degradation, confounding biomass and mono-temporal classification when the same species or habitat exhibits different spectra under different moisture conditions. Multi-temporal analyzes can separate short-term moisture fluctuations from long-term stress. NDWI capture variations in water content, improving the assessment of vegetation health (Gao, 1996; Kowalski et al., 2022). Additional conditions- snow, dew/fog/rain water droplets, and wind-flattened vegetation (especially relevant in grasses and crops), introduce further variability (Hajj et al., 2014).

Finally, phenology and management affect functional trait extraction (Iakunin et al., 2025) and can shift which spectral and textural features are most informative: Geographic location and management influence HNV diversity classes (Ludwig et al., 2025) and mowing regime affects the importance of VIs and textural metrics for species-richness estimation (Bazzo et al., 2024). Overall, multiple interacting drivers can obscure one another, making RS-based indicator monitoring in grasslands inherently challenging.

4.3.2. *Ground truth collection*

Ground truth data are essential for calibrating and validation RS models (Łągiewska et al., 2025). Authority monitoring programs are valuable sources but many conservation agencies still rely primarily on field-based approaches, creating mismatches between current field protocols and what sensors can reliably observe. Key issues include scale mismatch between small grassland plots and pixel footprints, and species-survey mismatch, as RS mainly captures the upper canopy while field inventories record all species. Improving linkage requires adapting monitoring design toward remotely observable indicators, accurate plot geolocation, and standardized numeric scales or classes compatible with sensor signals. For management monitoring, reference data often lack key metadata (e.g., biomass removed per cut) and rarely record grazing, grazing strategies (including rotational grazing), or other practices, limiting model training and evaluation. Integrating standardized ground-truth schemes that align with RS analyzes, (e.g., LUCAS, Eurostat, 2024) and complementary sources (e.g., webcams/phenocams) can strengthen reference datasets and improve operational monitoring.

4.4. *Outlook on new sensors and future applications*

Future grassland monitoring will likely shift toward climate-sensitive indicators, notably drought impacts (Kowalski et al., 2024) and phenological changes (Bellini et al., 2023). This motivates integrating climate and ecohydrological covariates for early warning and impact analysis, and quantifying resilience through stress recovery rates. Higher temporal resolution will be increasingly important to track phenology and extreme events.

Continuity of long time series (e.g., Sentinel and Landsat follow-on programs) and new sensors, including Copernicus Expansion missions (e.g., CHIME, LSTM, and ROSE-L) and NASA's SBG mission, will improve spatial, spectral, and temporal fidelity, strengthening inference on vegetation condition, traits, and stress processes (European Space Agency, 2024). Commercial constellations and drones add complementary high-resolution observations.

Drone-based deep-learning applications are promising but depend on enabling regulatory frameworks (Schnalke et al., 2025). Methodologically, the space-time trade-off will favor multi-sensor, multiscale fusion and automated, data-driven pipelines, reducing reliance on a small set of indices in favor of multimodal learning. Open archives, ready-to-use products, and large processing platforms will support method comparisons and robust error assessment.

Operationally, ready-to-use products can increase uptake by decision makers and enable site-specific, adaptive agri-environment- climate measures (e.g., flexible mowing restrictions aligned to local phenology and habitat needs). Synoptic monitoring supports landscape-scale decisions and strengthen implementation under the Common Agriculture Policy and Habitats Directive by complementing costly field inspections (Corbane et al., 2015; European Union, 2021).

5. Conclusion

Grassland RS applies spectral, structural, temporal, and spatial indices to assess environmental indicators, with NDVI still dominant. In European grasslands, RE/chlorophyll-sensitive indices consistently outperform simple greenness metrics for biomass, but saturation, background effects, and site dependence persist, requiring local validation and uncertainty assessment. Biodiversity and habitat applications benefit more from spectral-variability metrics, hyperspectral trait proxies, and phenology/texture features than single VIs. Mowing is best detected from time-series breakpoints, ideally with SAR support. Carbon fluxes benefit from SIF/NIR plus meteorological data; water fluxes/stress from NDWI/MSI and LST-based ET proxies, and phenology from dense time-series. Habitat classification improves by integrating phenology, structural (SAR/LiDAR), and RE information, while spatial/temporal indices remain underused.

Overall, indices are indirect proxies leaving a persistent signal-indicator gap. Key limitations include saturation, background/mixed-pixels, phenology/disturbance sensitivity, limited ecological specificity, and scaling/transferability constraints.

Future European work should move beyond greenness toward biodiversity-relevant, policy-ready indicators validated with standardized field data, while aligning compliance protocols (e.g., NATURA 2000) and class definitions with RS-observable properties.

CRediT authorship contribution statement

Ann-Kathrin Holtgrave: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Michael Förster:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Conceptualization. **Christine Wallis:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **María Dolores Raya-Sereno:** Writing – review & editing, Writing – original draft, Investigation. **Vicente Burchard-Levine:** Writing – review & editing, Writing – original draft, Investigation. **Julien Morel:** Writing – review & editing, Writing – original draft, Investigation. **Mattia Rossi:** Writing – review & editing, Writing – original draft, Investigation. **Duccio Rocchini:** Writing – review & editing, Writing – original draft, Investigation. **Marcel Schwieder:** Writing – review & editing, Writing – original draft, Investigation. **Patrick Hostert:** Writing – review & editing, Writing – original draft, Conceptualization. **Fabian Faßnacht:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Birgit Kleinschmit:** Writing – review & editing, Writing – original draft, Supervision, Investigation, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT (OpenAI, 2025) and Writefull for Overleaf (Writefull, 2025) in order to improve the readability and language of the manuscript. After using these services, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2026.114732.

Data availability

No data was used for the research described in the article.

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