Remote Sensing of Grassland Biodiversity and Functional Traits

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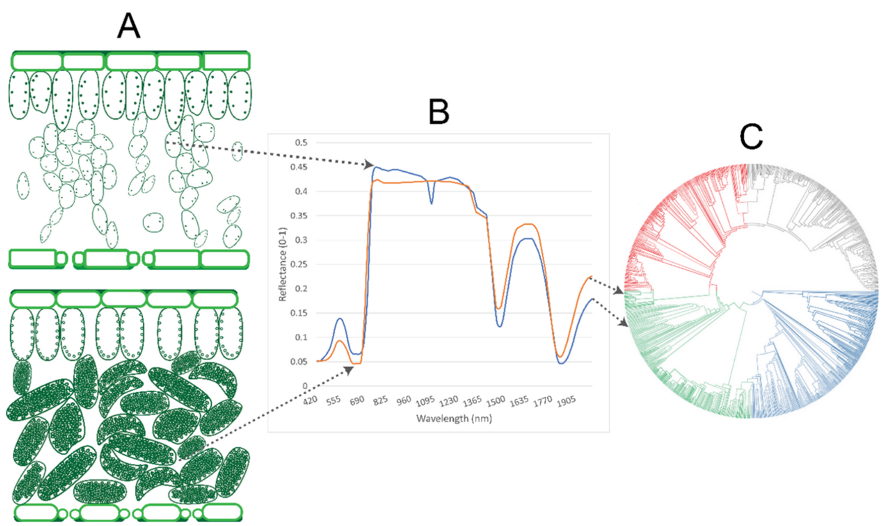
Abstract

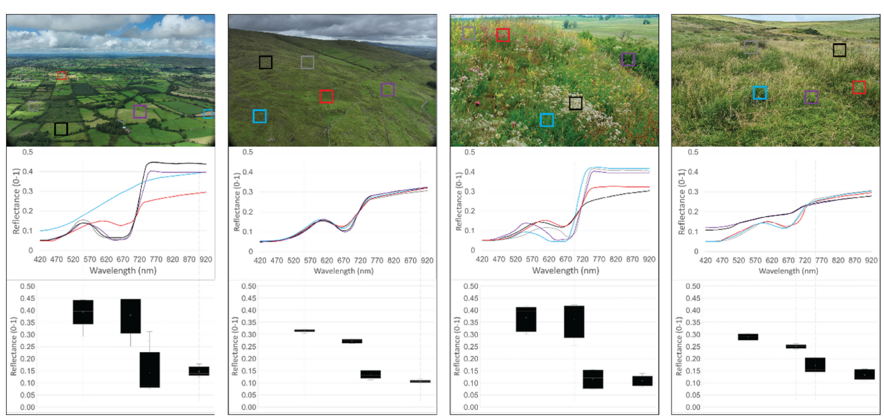
Grasslands cover between 30 and 40% of the world's land surface and, despite providing numerous ecosystem services and being rich in biodiversity, are increasingly under threat and shrinking in coverage. As such, the development and application of monitoring techniques are of vital importance. The use of remotely sensed imagery for the monitoring of both biodiversity and functional traits in grassland ecosystems has increased substantially in the last few decades. More recently, uncrewed aerial vehicles (UAVs) have begun to play an increasingly important role, acting as a bridge between the decameter satellite imagery and the point scale data collected on the ground. The use of UAV-mounted hyperspectral sensors, covering up to hundreds of spectral bands, has become particularly popular as the senor sizes have reduced, and UAV technology has improved. Here, we provide a review of the latest remotely sensed monitoring methods for both biodiversity and functional traits using multispectral and hyperspectral sensors. We highlight the key innovations that have occurred (e.g., use of point cloud data, identification of error sources), the bottlenecks to and opportunities for further development. UAV surveys show particular promise for monitoring functional traits. We conclude that UAV methods offer the opportunity to scale surveys from individual sites to regional areas, and can aid in refining satellite-based observations to improve the monitoring of grassland ecosystems at national and global scales.

Introduction

Grasslands cover 30 to 40% of the Earth's land surface (Blair et al., 2014) and are responsible for up to a third of net primary productivity on land (Vitousek, 2015), providing many important ecosystem services, from water flow regulation and purification to erosion control and pollination (Bengtsson et al., 2019: Peciña et al., 2019). Grasslands also contribute significantly to livestock farming through grazing and fodder production (Erb et al., 2016). Natural and semi-natural grasslands are often characterised by high community complexity (Wilson et al., 2012), making them important sources of, and contributors to, biodiversity (Russo et al., 2022). Surveys carried out on experimental plots have shown that increased grassland biodiversity can contribute to greater yields, improved yield stability and increased carbon sequestration (Finn et al., 2013; Isbell et al., 2015; Lange et al., 2015; Craven et al., 2018; Haughey et al., 2018). However, through land-use change, abandonment, urbanisation and intensive agriculture, natural and semi-natural grasslands have become endangered ecosystems (Pärtel et al., 2005; Johansen et al., 2022) with decreases in their area and reductions in their biodiversity in recent decades (Henle et al., 2008; O'Mara, 2012; Newbold et al., 2016). In addition to the diversity of species, plant functional traits (biochemical, physical and morphological properties that affect fitness in response to the environment) and trait diversity are key features of (semi-)natural grasslands. For example, traits such as high leaf dry matter content (LDMC), low specific leaf area (SLA) and low leaf nitrogen content indicate stress tolerance strategies of grass species and adaptation to low temperature and low precipitation (Wingler and Sandel, 2023). The relationship between such plant functional traits and their role in ecosystem functioning and ecosystem services (e.g., water regulation, carbon storage, stress tolerance) are well-established (Diaz and Cabibo, 2001; Kattge et al., 2011; Tilman et al., 1997). However, how diversity of functional traits determines stress resilience is not fully understood (Miller et al., 2019). In order to preserve current (semi-)natural grasslands, protect biodiversity and ensure the continuation of important ecosystem services, methods to monitor the biodiversity and functional traits of existing grassland ecosystems is vitally important. Surveys of plant biodiversity and functional traits traditionally involved the detailed manual examinations of small plots within a site, a time- and labour-intensive activity, followed by extrapolation across the entire site (Stroh et al., 2020). These methods are ill-suited to surveying larger areas or for repeat, long-term national monitoring. Remote sensing offers the ability to monitor biodiversity across a range of scales, from metres to kilometres, in a consistent and repeatable manner. The physical and chemical properties of plants influence how sunlight interacts with them. By examining the absorption and reflection of light across different parts of the electromagnetic spectrum, information about the species diversity (Figure 1) (Wang and Gamon, 2019), functional traits (Homolová et al., 2013) and thus α-diversity (diversity at a local scale) and β-diversity (ratio between regional and local diversity) can be extracted.



Recent technological advances make satellites increasingly suited to grassland monitoring, even across the relatively small and fragmented natural and semi-natural grasslands in Europe. Additionally, instruments can be mounted on aircraft to provide multispectral (typically up to a dozen discrete spectral bands) or hyperspectral (100s or of under a meter. Furthermore, developments in Uncrewed Aerial Vehicle (UAV) technology now allows similar data to be captured at spatial resolutions down to millimetres.



The most common method of mapping grassland biodiversity comes from the spectral variation (SV) hypothesis. This method assumes that the variability in the spectral signal detected by the remote sensing instrument is correlated with biodiversity (Rocchini et al., 2004). This can be performed with both multi and hyperspectral instruments and can be used to assess biodiversity across a landscape and within plots from individual sites (Figure 2). Additional methods for monitoring both biodiversity and functional traits include the use of different spectral and vegetation indices, 3D data such as from LiDAR or structure from motion (SfM), data fusion between high spatial resolution imagery and that with greater spectral information, or spectral data combined with 3D (Aasan et al., 2015; Gašparović et al., 2019; Laliberte and Rango, 2011).

For this review, a Google Scholar search was conducted for studies between 2018 and 2024 with the search terms "remote sensing", "grasslands" and "biodiversity", and a separate search replacing "biodiversity" with "functional traits". The publications that included all the search terms and were directly related to the topic were examined in further detail and their references checked for additional publications. This resulted in 37 publications, 20 related to biodiversity, 15 on functional traits, and two studies with a focus on both biodiversity and functional traits (Table 1).

Table 1: List of the main grassland biodiversity and functional trait remote sensing studies used for this review.

Biodiversity	Functional Traits	Biodiversity & Functional Traits
Hyperspectral imaging		
Rocchini et al., 2010	Capolupa et al., 2015	Tang et al., 2021
Wang et al., 2016	Aasen et al., 2015	
Gholizadeh et al., 2018	Schweiger et al., 2017	
Gholizadeh et al., 2019	Näsi et al., 2018	
Gholizadeh et al., 2020	Wang et al., 2019	
Lyu et al., 2020	Wijesingha et al., 2020	
Yang and Du, 2021	Zhao et al., 2021a	
Xu et al., 2022	Zhang et al., 2022	
Thornley et al., 2023	Gholizadeh et al., 2022	
Multispectral imaging		
Lallibet and Rango, 2011	Li et al., 2018	Zhao et al., 2021b
Mansour et al., 2015	Imran et al., 2020	
Lu and He, 2017	Grüner at al., 2020	
Lopes et al., 2017	Grüner at al., 2021	
Sun et al., 2018	Rakotoarivony et al., 2023	
Shoko et al., 2020	Zhao et al., 2024	
Fauvel et al., 2020		
Conti et al., 2021		
Rossi et al., 2022		
Yang et al., 2023		
Pöttker et al., 2023		

Remote Sensing of Grassland Biodiversity

Hyperspectral Remote Sensing of Grassland Biodiversity

Hyperspectral instruments are most typically mounted on crewed aircraft for most grassland studies. Some satellites, such as Hyperion, have carried hyperspectral sensors, while in recent years a growing number of studies have made use of UAVs for carrying hyperspectral instruments. Each approach has drawbacks in terms of spatial resolution, spatial coverage, positioning and accuracy. A good agreement was found between airborne (crewed aircraft) hyperspectral data, spatial resolution and species turnover (β-diversity) in a highland savanna (Rocchini et al., 2010). However, spectral diversity in the smaller sampling areas (100 m^2) produced a less robust correlation with β-diversity than in the larger sampling area, 1,000 m^2, probably due to increased noise when using smaller grain sizes. Focusing on α-diversity (richness and Shannon's Diversity index), Wang et al. (2016) found a strong positive relationship between biodiversity and productivity, and between optical diversity and species diversity for a Canadian prairie using airborne hyperspectral data, ground sampling and eddy covariance measurements. Comparing spectral diversity, recorded via a tram system, with a range of biodiversity metrics at an experimental prairie test site indicated that a resolution of 1 to 10 cm is best, and spectral diversity correlated differently with different biodiversity metrics (Wang et al., 2018). Spatial resolution also affects the confounding impact of bare soil on the correlation between remote sensing measures of species richness, and, depending on the resolution, different methods to account for bare soil need to be applied (Gholizadeh et al., 2018). Gholizadeh et al. (2019) assessed α-diversity in restored grassland plots in Nebraska that had been seeded with native prairie grasses, some of which were old and contained invasive species while others were younger and mainly contained grasses of the original study design. Ground based (quadrats) and airborne hyperspectral surveys were used. In young plots, spectral diversity was strongly related to α-diversity, but in old plots the relationship was not significant. The relationship between hyperspectral measures of biodiversity and ground surveys varied from one year to the next and weakened over the growing season – emphasising the need for multitemporal measures of grassland biodiversity (Gholizadeh et al., 2020). Lyu et al. (2020) combined a handheld spectrometer, Hyperion and Landsat data for species mapping to assess grassland degradation in Mongolia. This was achieved by comparing the relative proportions of different grass species, extracted from Hyperion data, with ground surveys and metrics derived from Landsat imagery, such as above ground biomass (AGB), net primary productivity and vegetation coverage. By focusing on the identification of typical and indicator species only, classification accuracies of over 70% were achieved. Utilising a UAV mounted hyperspectral sensor, Yang and Du (2021) classified plant species in a desert steppe ecosystem in inner Mongolia. They used a large variety of vegetation indices and decision tree classification to detect plant species with 87% accuracy. In an Alpine steppe nature reserve, Xu et al. (2022) compared four spectral metrics from a UAV mounted spectrometer with two species diversity indices (species richness and the Shannon–Wiener index). The authors found that the relationships between spectral diversity and species diversity were significantly strengthened when bare soil was filtered from the survey data. Finally, a meta-analysis of grassland biodiversity predictions from spectral diversity metrics found an overall correlation coefficient of $r = 0.36$ across studies (Thornley et al., 2023). The authors noted high levels of variability both within and between studies, with leaf spectra producing a stronger relationship than overall canopy spectra. Surveys of arid, tropical and southern hemisphere sites were lacking, and more scalable and multitemporal studies are required to reduce the uncertainty in the SV/biodiversity correlations.

Multispectral Remote Sensing of Grassland Biodiversity

RGB cameras capture light across the visible wavelengths, while multispectral instruments typically capture a few additional discrete wavelengths of light in the near and shortwave infrared range, meaning that less information can be derived regarding the surface under observation when compared with hyperspectral instruments. However, they are in use on many more satellites resulting in a multi-decadal record of observations on platforms such as the Landsat series. Furthermore, they are cheaper and smaller than hyperspectral cameras, making them more accessible and suitable to consumer grade UAV use. While examining the degradation of grasslands in South Africa, Mansour et al. (2015) employed field sampling, SPOT 5 data and random forest machine learning classification. Indicator species were identified and used to assess the level of degradation. The identification of indicator species was improved from 75 % to 89% when ground-based edaphic measurements were integrated with SPOT 5 data. Lu and He (2017) used a UAV with a near infrared (NIR)-GB camera to map tall grassland species in southern Canada at 5 cm resolution. The authors achieved an accuracy of 85% overall (averaged across all dates and species surveyed) using object-based classification, but suggest that this accuracy can be improved with more precise instruments and a greater number of spectral bands. Across 200 sites in southwest France, Lopes et al. (2017) used a timeseries of SPOT 5 derived NDVI over 18 dates, and a combination of the eight Sentinel 2 bands across eight dates to predict biodiversity. Results, compared to the Shannon and Simpson indices were poor, suggesting that high temporal resolution, moderate-high spatial resolution and multispectral data are not suited to mapping biodiversity at the grassland scale. In Alpine meadows on the Tibetan Plateau, Sun et al. (2018) flew a UAV at just 2 m elevation for highly detailed imagery. Plant species in each image were manually identified and compared to ground-based quadrat surveys and with a range of species composition indices. The UAV surveys proved highly effective compared with indices derived from traditional methods (r^2 values between 0.726 and 0.872), while also covering a larger, more representative area and measuring a greater number of species. Shoko et al. (2020) attempted to differentiate between C_3 and C_4 species (*Festuca costata and Themeda triandra*) in South Africa using multidate Sentinel 2 data. The authors achieved greater accuracy in winter (between 91.8% and 95.3%), than summer (between 81.4% and 90.3%). Using Sentinel 1 (Synthetic Aperture Radar) and Sentinel 2, in combination with ground surveys, Fauvel et al. (2020) measured and predicted plant diversity metrics in terms of richness indices, diversity indices and some functional indices in grasslands in southwest France. The methods used worked better for Simpson and Shannon indices than richness indices, and moderately well for functional indices. Incorporating Sentinel 1 data did not significantly improve predictions. In Conti et al. (2021) the authors assessed the links between spectral and taxonomic diversity, and vertical complexity, using a UAV mounted multispectral sensor in a mesic meadow in South Bohemia, Czech Republic. It was found that the relationship between spectral and taxonomic diversity was mediated by grassland vertical complexity - the more pronounced the vertical complexity, the more negative the relationship between taxonomic and spectral diversity. On Alpine grasslands, Rossi et al. (2022) flew a UAV with a consumer grade camera and combined the imagery with airborne hyperspectral surveys. The fused data set tested the effects of spatial resolution and a variety of spectral metrics on measuring species diversity. The authors found the fused dataset worked well but also produced a surprising finding – that spectral metrics centred on spectral complexity was negatively correlated with species richness. The authors, note that the presence of live and dead biomass acted as significant confounding variables in their correlations. On a semi-natural meadow in Saxony, Germany, Pöttker et al. (2023) achieved accuracies of up to 88% by using ground surveys and a multispectral UAV in combination with convoluted neural networks to map plant communities. Yang et al. (2023) combined ground sampling, environmental data and MODIS imagery to predict biodiversity and AGB in the Qinghai–Tibet Plateau grasslands using a random forest model, achieving and r^2 of 0.60 for their plant species diversity model.

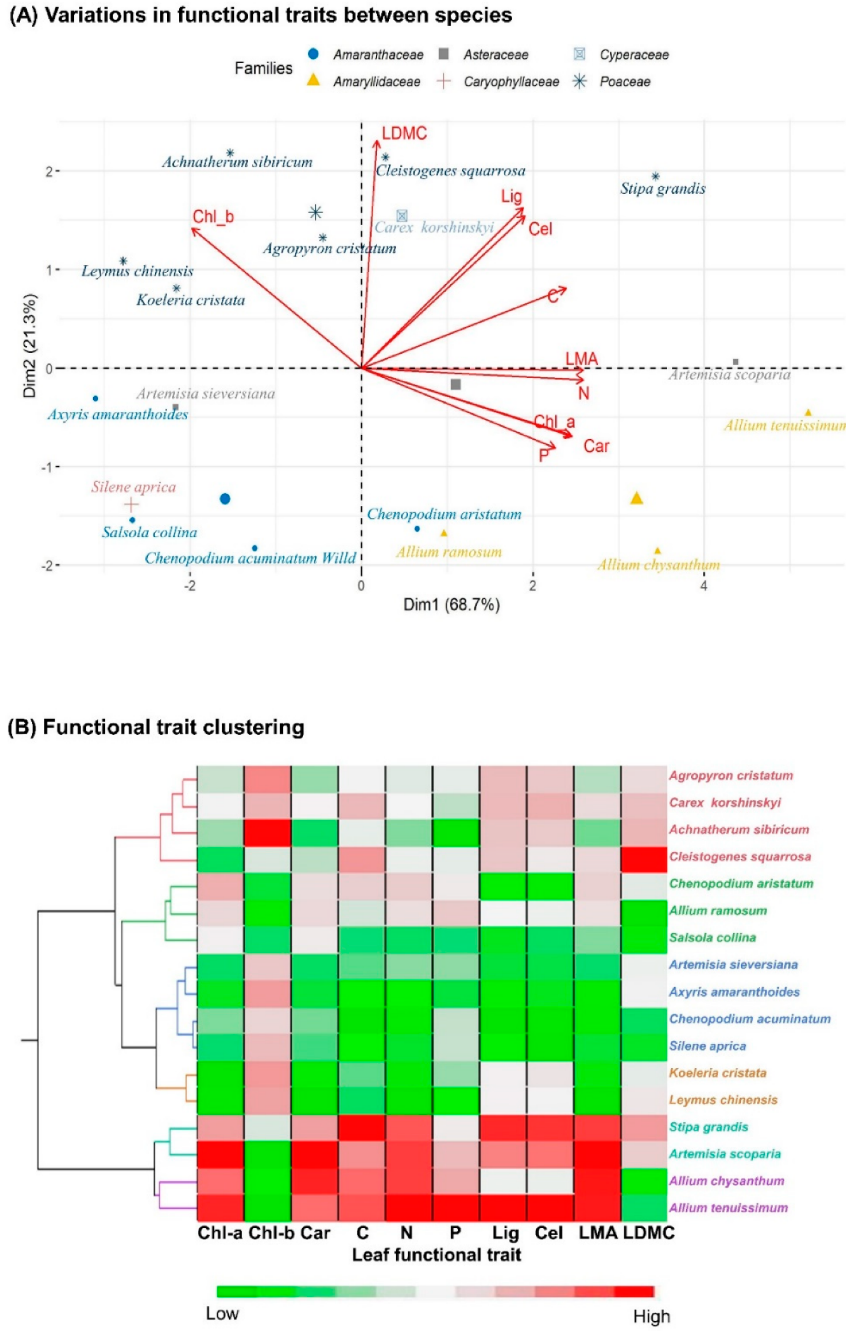
Remote Sensing of Grassland Functional Traits

Hyperspectral Remote Sensing of Grassland Functional Traits

On experimental grassland sites in Germany, Capolupo et al. (2015) used a UAV mounted hyperspectral camera and ground-based surveys to examine a range of physical and chemical traits (e.g., height, biomass, crude protein, nitrogen, potassium, etc). To estimate these traits, the authors used two methods, partial least squares regression (PLSR) and vegetation indices. PLSR performed well for both physical and chemical traits, while vegetation indices worked well only with physical traits. In a separate experimental barley site in Germany, Aasen et al. (2015) combined 3D with hyperspectral imagery for precision agriculture. Plant height, chlorophyll, leaf area index (LAI) and biomass were measured with r^2 values of 0.7, 0.52, 0.32 and 0.29, respectively. Airborne hyperspectral surveys were used over Swiss alpine grasslands, in combination with ground surveys, to examine links between community traits, functional traits and spectra with PLSR. The authors noted some inconsistent results with plant life and growth forms, but functional type modelling produced more consistent results (Schweiger et al., 2017). In a barley test site in Finland, Näsi et al. (2018) equipped a UAV with hyperspectral and RGB cameras. The authors combined the digital surface model and digital terrain model, generated with using SfM, with the hyperspectral information, estimating dry and fresh matter, and nitrogen content. The 3D data combined with RGB information was nearly as accurate as hyperspectral data for biomass, but hyperspectral imaging performed better for nitrogen content. Wang et al. (2019) used ground sampling and airborne hyperspectral surveys to map foliar functional traits across a grassland experimental site in Minnesota. They used PLSR and gaussian processes regression (GPR) for modelling, uncertainty and performance. Both regression methods produced similar results, with leaf mass per area, soluble cell contents, hemicellulose and cellulose all producing r^2values > 0.8, while models for the contents of lignin, nitrogen and some pigments performed more poorly. Across eight grassland sites in Northern Germany, Wijesingha et al. (2020) attempted to predict forage quality by mapping crude protein and acid detergent fibre using hyperspectral airborne surveys. Five predictive modelling methods were assessed PLSR, random forest regression, GPR, support vector regression and cubist regression. Support vector regression performed best for crude protein, while cubist regression performed best for acid detergent fibre. In an Inner Mongolian monoculture test site, Zhao et al. (2021a) used a UAV mounted spectrometer to measure chemical traits (carbon, nitrogen, phosphorus, lignin, cellulose, and chlorophyll a and b). They successfully measured numerous functional traits and noted that retrieval worked better on an area basis rather than mass basis. Certain traits could also be used effectively as predictors of AGB across the monoculture sites. In mixed grasslands on the Tibetan Plateau, UAV hyperspectral surveys were used by Zhang et al. (2022) to map functional traits. Algorithms used were PLSR, the generic algorithm integrated with the PLSR, random forest (RF) and extreme gradient boosting (XGBoost). Chlorophyll a, chlorophyll b, carotenoid content, starch content, specific leaf area and leaf thickness were estimated well (r^2 values between 0.64 and 0.8), while nitrogen content, phosphorus content, plant height and leaf dry matter content were modelled with lower accuracy (r^2 values between 0.3 and 0.54). Finally, Gholizadeh et al. (2022) used aerial spectroscopy (1 m resolution) to map 12 functional traits and use these to differentiate an invasive grassland species, *Lespedeza cuneata* , from other species in a tallgrass prairie site in Oklahoma. They achieved an accuracy on 94%, showing that functional trait measurements can be used to identify invasive species. However, the accuracy was lower in species-rich grasslands.

Multispectral Remote Sensing of Grassland Functional Traits

On the Qinghai-Tibetan Steppe, Li et al. (2018) used Landsat 8 and Sentinel 2 to map plant functional traits at the community level - canopy chlorophyll, specific plant area and plant dry matter content. The authors used field sampling in combination with vegetation indices and statistical modelling, with google earth engine, and achieved moderately good results (r^2 from 0.22 to 0.53). Imran et al. (2020) used ground-based hyperspectral measurements to simulate Sentinel 2 and 3 imagery, utilising red edge and NIR vegetation indices to map LAI in grasslands in northern Italy and Austria. They found that LAI retrieval is strongly influenced by plant traits, physical and chemical (e.g., AGB, leaf angle distribution, brown pigment content and chlorophyll content). Over an experimental site in northern Germany, Grüner at al. (2020) used UAV multispectral data, with PLSR and RF regression, for predicting aboveground biomass and nitrogen fixation in legume-grass mixtures. While consistent estimates of biomass were achieved using RF and the results for nitrogen fixation were also strong, the most effective regression method depended on the specific legume/grass proportions in the test site. In a subsequent study, at the same location, Grüner at al. (2021) combined a terrestrial laser scan survey with a multispectral UAV survey (including texture analysis) to measure fresh and dry matter (biomass) and nitrogen fixation in legume grass mixtures. The fusion approach proved to be a significantly better predictor, overcoming the limitation of each separate sensor. For nitrogen fixation, the multispectral sensor had a relative root mean squared error of prediction (rRMSEP) of 17.64%, with a rRMSEP of 20.07% for canopy surface height and 14.4% for the sensor fusion. Rakotoarivony et al. (2023) used field sampling to identify unique functional traits that distinguishes*L. cuneata* from the native grassland species. Next, airborne hyperspectral data was used to identify the vegetation indices most closely related to these traits, and PlanetScope multispectral satellite imagery was then used to identify and map *L. cuneata* across a 47 km^2 region of U.S., with an accuracy of over 80%. Across three grassland sites in Inner Mongolia, Zhao et al. (2024) used field sampling to identify 13 functional traits and associated these traits with leaf spectra through PLSR. PLSR was also applied to twelve bands, 30 vegetation indices and convex hull volume from Sentinel 2 imagery to map function diversity on a large scale. All but one of the functional traits (carbon) were predicted reasonably well from the Sentinel 2 imagery, with r^2 values of between 0.32 and 0.82.



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Conclusions

This review has examined the remote sensing of grassland biodiversity and functional traits with a focus on recent technological and methodological developments. Advances in UAV technology have accelerated the increase in grasslands surveys featuring very high spatial resolutions, with 3D components and increasingly employing multispectral and hyperspectral sensors. As UAV technology continues to improve and become more accessible through cheaper costs and automated flight controls, and survey and processing methods mature, UAVs are likely to become a standard tool in grassland surveys. UAV surveys can also bridge the gap between ground-based fieldwork and satellite remote sensing, as well as providing ground truthing for spaceborne data, potentially refining the seemingly inconsistent relationship between spectra variation and biodiversity. This can aid in the development of satellite remote sensing methods and allow the scaling of biodiversity and functional trait surveys from discrete points to site-wide and national surveys.

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Authors' Contribution Statement

SH, FC and AW conceive the ideas. SH led the writing of the manuscript, with early input from AW. All authors contributed critically to the drafts and gave final approval for publication.

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1 Data Availability Statement The main research papers reviewed in this article are included in Table 1. All papers are cited throughout the document and included in the references section.

1 Data Availability Statement

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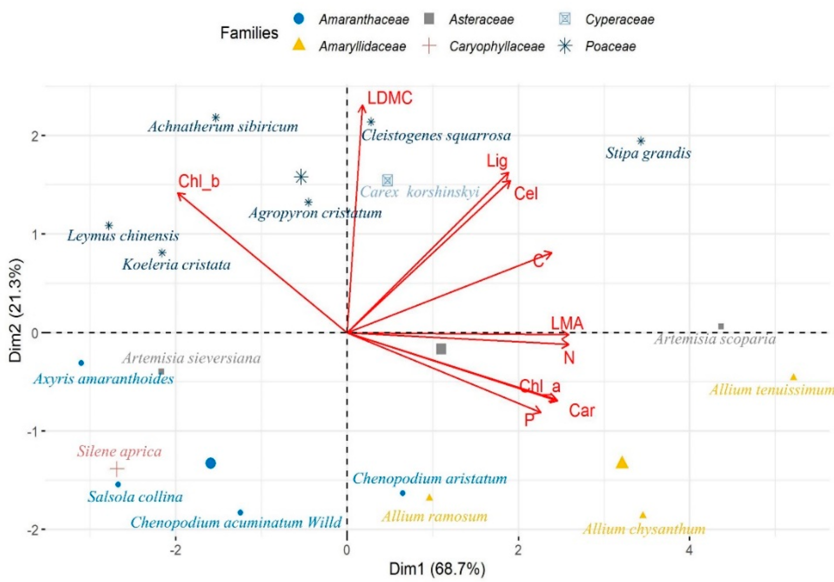
Table 2: List of the main grassland biodiversity and functional trait remote sensing studies used for this

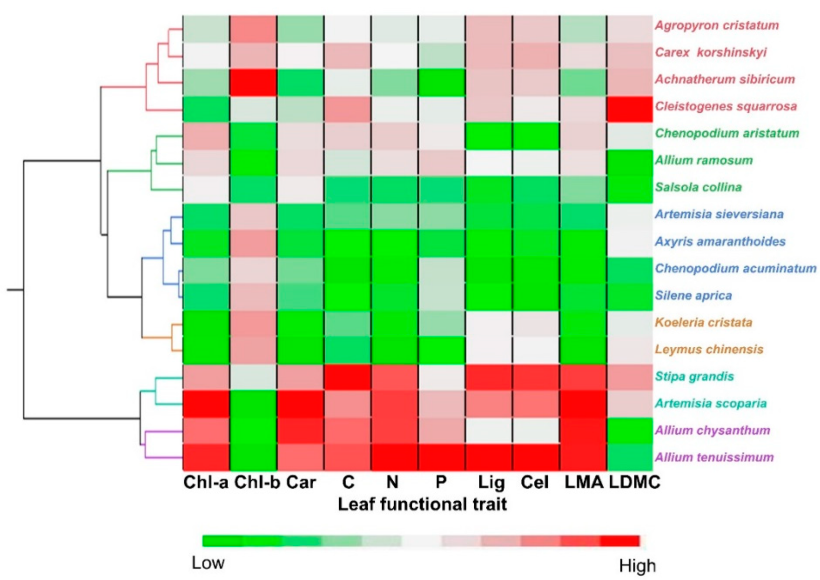
review

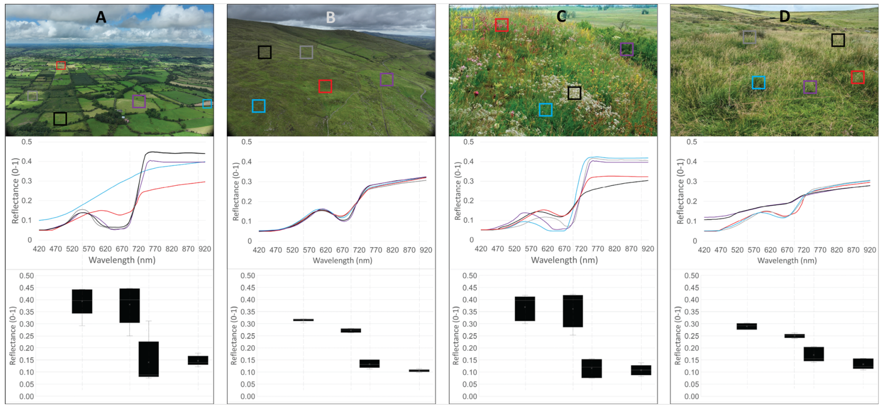
Biodiversity	Functional Traits	Biodiversity & Functional Traits
Hyperspectral imaging		
Rocchini et al., 2010	Capolupa et al., 2015	Tang et al., 2021
Wang et al., 2016	Aasen et al., 2015	
Gholizadeh et al., 2018	Schweiger et al., 2017	
Gholizadeh et al., 2019	Näsi et al., 2018	
Gholizadeh et al., 2020	Wang et al., 2019	
Lyu et al., 2020	Wijesingha et al., 2020	
Yang and Du, 2021	Zhao et al., 2021a	
Xu et al., 2022	Zhang et al., 2022	
Thornley et al., 2023	Gholizadeh et al., 2022	
Multispectral imaging		
Lallibet and Rango, 2011	Li et al., 2018	Zhao et al., 2021b
Mansour et al., 2015	Imran et al., 2020	
Lu and He, 2017	Grüner at al., 2020	
Lopes et al., 2017	Grüner at al., 2021	
Sun et al., 2018	Rakotoarivony et al., 2023	
Shoko et al., 2020	Zhao et al., 2024	
Fauvel et al., 2020		
Conti et al., 2021		
Rossi et al., 2022		
Yang et al., 2023		
Pöttker et al., 2023		

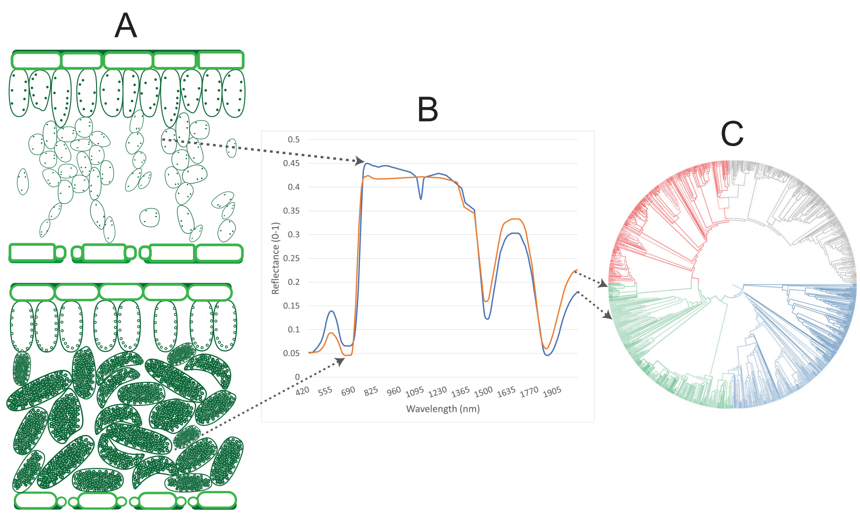
(A) Variations in functional traits between species

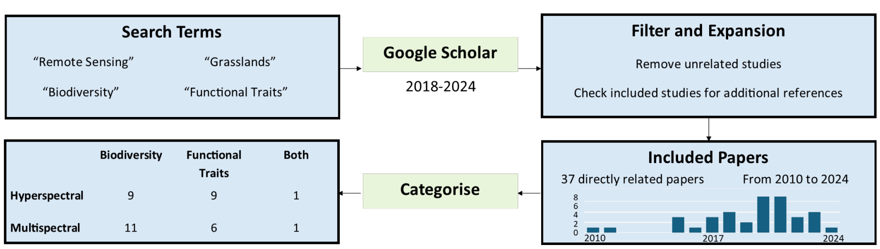


(B) Functional trait clustering




A
B
C
D
Reflectance (0-1)
Wavelength (nm)


A
B
C
Reflectance (0-1)
Wavelength (nm)


Search Terms
"Remote Sensing"
"Grasslands"
"Biodiversity"
"Functional Traits"
Google Scholar
2018-2024
Filter and Expansion
Remove unrelated studies
Check included studies for additional references
Included Papers
37 directly related papers
From 2010 to 2024
Categorise
Biodiversity
Functional Traits
Both
Hyperspectral 9 9 1
Multispectral 11 6 1