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From Field Spectra to Shared Knowledge: Harmonizing Hyperspectral Reflectance Data for Ecological Insights

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Abstract

The massive stream of hyperspectral Earth Observation (EO) data presents huge opportunities for vegetation remote sensing. Recent advances in machine learning and foundational models have demonstrated a remarkable capacity to retrieve plant functional traits directly from spectral reflectance. Field spectroscopy provides the critical link between hyperspectral EO and plant functional traits. It delivers ground reference data on which trait-retrieval models depend. Yet, the full potential of existing spectroscopic datasets remains largely unreleased, owing to fragmented data distribution, inconsistent documentation, and heterogeneous

preprocessing practices across the community. Here, we present a harmonised spectral library for Arctic tundra vegetation. Compiled from more than 100 hyperspectral datasets and spanning 25 years of field campaigns, we integrated $\approx 32,000$ hand-measured vegetation reflectance spectra. Based on more than 600 working hours, our efforts revealed recurring, systematic challenges in data discoverability, metadata completeness, geospatial and temporal reporting, and pre-processing transparency. We document these challenges, identify their consequences for machine learning applications, and derive a practical checklist of minimum standards for field spectroscopy data collection, documentation, and sharing. Although grounded in the Arctic biome, the harmonisation workflow and recommendations are transferable across vegetation types and sensor configurations. This contribution aims to raise community awareness and promote the open data practices needed to fully realise the ecological potential of the hyperspectral era.

Keywords: spectral library, hyperspectral data, field spectroscopy, data harmonization, benchmarking dataset, FAIR data, machine learning, Arctic tundra, Antarctic vegetation

1 Introduction

Spectroscopy, the measurement of reflected light across hundreds of contiguous, narrow wavelength bands, has recently emerged as an operational tool in Earth Observation (EO). This tool offers ample opportunities to boost our abilities to observe the composition and the status of ecosystems across the Earth’s surface. While multispectral sensors capture only a handful of broad spectral bands, hyperspectral sensors resolve the full optical spectrum at fine spectral resolution, encoding detailed biochemical and structural information about vegetation that broadband sensors fundamentally cannot retrieve [1, 2]. Early hyperspectral instruments were largely confined to airborne platforms and experimental campaigns. The launch of hyperspectral satellites marked a turning point. Nowadays, globally accessible, freely available hyperspectral imagery with increasing quality due to improving noise reduction is scientific reality [3]. This transition is set to accelerate further with the Copernicus Hyperspectral Imaging Mission for the Environment (CHIME), an upcoming ESA mission that will provide systematic, high-revisit hyperspectral coverage of the Earth’s land surface [4]. Together, these missions represent the foundation of a new era in vegetation remote sensing that generates data volumes and spatial coverage that no traditional empirical analysis pipeline can realistically process.

Machine learning (ML) offers a promising path to exploiting this expanding hyperspectral data stream. Algorithms ranging from random forests to deep neural networks have demonstrated remarkable capacity to retrieve plant functional traits directly from spectral reflectance [5–7]. Current advances in foundational models direct towards promising future research in this field. Yet the performance, generalisability, and ecological credibility of these models are fundamentally constrained by the quality, quantity, and representativeness of the training data used to build them. Without

high-quality, well-characterised ground reference data, even the most sophisticated ML model risks learning spectral artefacts rather than meaningful ecological signals [8]. The bottleneck in hyperspectral vegetation science is therefore not satellite data but the ground reference.

Among the most insightful ecological targets that hyperspectral remote sensing is able to retrieve are plant functional traits, i.e. different measurable characteristics of plant parts exposed to the sensor [9], such as leaf chlorophyll content, specific leaf area, leaf water content, or canopy structure [10]. Plant traits mediate the exchange of energy, water, and carbon between vegetation and its environment [11]. Moreover, they reflect the capacity of vegetation to adapt to environmental conditions and are therefore essential for modelling and understanding ecosystem processes, status and health [12, 13]. The distribution and diversity of traits across a plant community represents its functional identity across space and time. Exploring these patterns allows quantifying plant functional diversity, tracking shifts in vegetation composition under environmental change, and supporting biodiversity monitoring at scales far beyond what in-situ surveys alone can achieve. At the landscape level, spatially explicit spectral information forms the basis for mapping trait-based functional patterns, while conventional, multispectral vegetation indices such as the widely applied Normalized Difference Vegetation Index (NDVI, [14, 15]) continue to provide operational insights into ecosystem condition and vegetation health. Realising the full potential of hyperspectral data for plant trait retrieval and functional diversity monitoring at any of these scales requires that ML models are trained on ground reference data that is (i) well documented, (ii) precisely labelled, (iii) ecologically meaningful, (iv) spectrally accurate, and (v) broad enough in its coverage to support robust generalisation.

A successful integration of remote sensing and plant ecological concepts requires careful matching of spatial scales of in-situ plant trait data with space- or air-borne observations. Field spectroscopy is one useful bridge for linking canopy reflectance spectra to plant traits [16]. By measuring the spectral reflectance of individual leaves, plant canopies, or mixed vegetation under controlled or ambient illumination, the in-situ measurement of surface reflectance using hand-held instruments allows to capture optical signals that resemble reflectance spectra recorded by a space-borne sensor. Additionally, it delivers a resolution and ancillary information that allows to disentangle the physical and biological drivers of the spectral signal [17]. Despite obvious differences in viewing and illumination geometry as well as atmospheric influences, these measurements underpin the calibration and validation of airborne and satellite-borne sensors, enable the development and testing of radiative transfer models, and provide the labelled training data that ML models require to learn the mapping between spectral reflectance and plant traits [18]. At the landscape scale, combined with co-located trait measurements, field reflectance spectra support functional analyses that bridge in-situ ecology and landscape-level remote sensing [19, 20].

Despite the foundational importance of field spectroscopy, acquiring such data is labour-intensive, equipment-intensive, and often logistically demanding. Campaigns must handle rapidly changing illumination conditions, instrument thermal drift, imperfect reference panel measurements, and the challenge of ensuring adequate spatial and plant species-level replication within limited field time. These challenges are amplified

118 in remote or high-latitude regions: in the Arctic tundra, for instance, campaigns must
119 be compressed into brief seasonal windows, conducted across difficult terrain, and
120 managed under weather conditions that directly affect spectral measurements [21]. In
121 general, field spectroscopy datasets tend to be relatively small, collected under varying
122 protocols, and produced by research groups with different instrumentation, software,
123 and documentation practices.

124 In this study, we refer to the definitions by Schaepman-Strub et al. [22] in order to
125 describe the regarded reflectance quantities, where spectral radiance is the "radiant
126 flux in a beam per unit wavelength and unit area and solid angle". Reflectance data
127 are generated either as non-calibrated digital numbers (DN) or calibrated radiance
128 values. It is "the ratio of radiant exitance with irradiance" [22] and is expressed dimensionless on an interval from 0 to 1. By measuring the target object in relation to a
129 reference surface (i.e. a Spectralon(C) reference panel), vegetation or plant reflectance
130 can be constructed (i) as a plant canopy or single-species measurement under ambient
131 illumination (i.e. sun and sky), (ii) as a measurement of target and reference with
132 artificial illumination using a leaf clip or a high intensity reflectance probe (HIRP)
133 in the field, (iii) based on sampled material using a leaf clip or HIRP, or (iv) under
134 laboratory conditions using different setups.

135 A considerable body of field spectroscopy data has been accumulated by the ecological remote sensing community over the past three decades. However, its storage, accessibility, and documentation remain highly heterogeneous. Data are scattered across specialised repositories, such as PANGAEA (Data Publisher for Earth & Environmental Data, <https://www.pangaea.de/>), EcoSIS (Ecological Spectral Information System, <https://ecosis.org>), and the USGS spectral library (<https://www.usgs.gov/>), but also across journal supplementary materials, institutional servers, and private hard drives that are effectively inaccessible to the broader community. Datasets that are publicly available commonly exhibit inconsistencies in file formats (e.g. proprietary instrument output versus plain-text ASCII or CSV exports), metadata completeness and structure, pre-processing choices (e.g. spectral smoothing, interpolation, reflectance calibration procedures), and measurement protocols (e.g. illumination geometry, reference panel type and frequency, replication schemes, and target definition). This heterogeneity is not merely an inconvenience and has been addressed
149 by the efforts for establishing standardized protocols in the past [23, 24]. It directly
150 undermines the reproducibility of spectroscopic analyses, limits cross-study and cross-biome comparability, restricts the transferability of trained ML models to new sites or sensors, and makes automated data integration - a prerequisite for assembling the large, diverse training sets that modern ML requires - exceptionally difficult.

155 This study grows from a concrete and ambitious effort: the assembly of a harmonised
156 hyperspectral benchmarking dataset for Arctic tundra vegetation, designed to train
157 ML algorithms for plant trait retrieval from hyperspectral imagery. To construct it,
158 we compiled and harmonised 111 individual spectral datasets from 74 sources, spanning field campaigns conducted between 1999 and 2023 by different research groups
159 across multiple Arctic and Antarctic sites, integrating a total of 31,647 hand-measured
160 vegetation reflectance spectra. Although built on a specific application, the challenges
161 we encountered, and the solutions we developed, are universal. The workflow we
162

describe for gathering, evaluating, and harmonising field spectroscopy data is generalisable across biomes, sensor types, and ecological applications. Here, we use the Arctic benchmarking dataset as an exemplary case to make those challenges concrete and tangible.

Based on this experience, we identify and structure the recurring technical, structural, and conceptual obstacles that arise when integrating large, multi-source spectral datasets. From these, we derive practical recommendations for field spectroscopy data collection, pre-processing, documentation, storage, and sharing. Our broader goal is to raise awareness within the hyperspectral vegetation community of the hidden costs of inconsistent data practices, and to advocate for workflows that serve both the data collectors who invest in field campaigns and the data users, including ML practitioners, who depend on the resulting datasets. In doing so, we hope to contribute to the development of more robust spectral libraries and benchmarking datasets that can fully leverage the hyperspectral EO era now underway.

2 Results

2.1 The Spectral LiBroyRy: a hyperspectral dataset for Arctic tundra vegetation

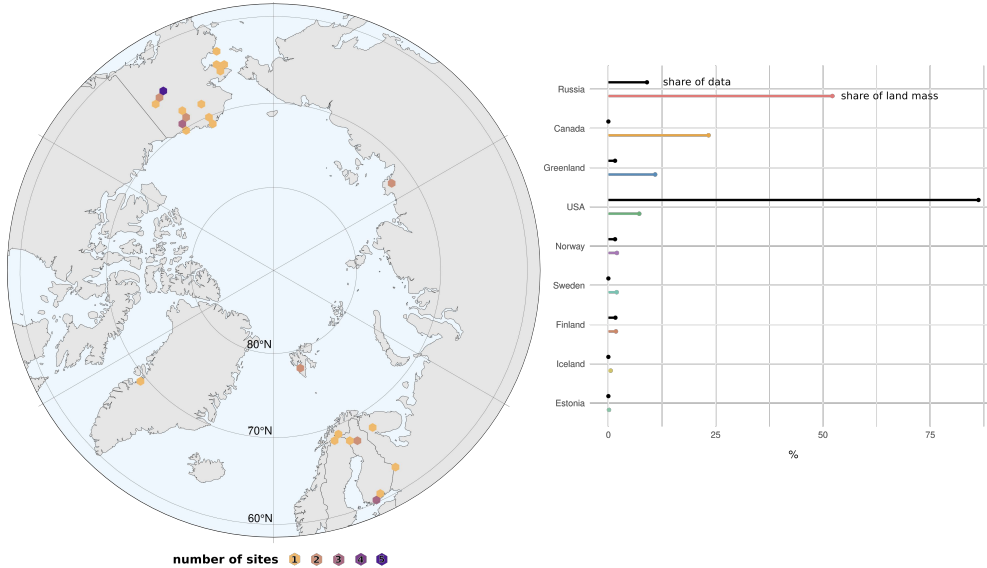


Fig. 1 Left side: spatial distribution of sampling sites across the Arctic region (60°N - 90°N) represented in the hyperspectral dataset shown as hexagonal binning of site density. Hexagon colour intensity reflects the number of sites per ≈ 100 km hexagonal bin, with darker colour indicating higher site density. Country borders are shown in grey. Right side: the percentage share of landmass on total Arctic land by country (coloured lines) compared to the percentage share of measurements by country (grey lines). Data from Antarctica are shown in a separate map in the Appendix (Figure A1). Projection: polar stereographic.

180 The presented spectral library integrates numerous hyperspectral measurements
181 from 109 datasets across the Arctic region (Figure 1 left) and two datasets including
182 ≈ 520 individual measurements from Antarctica (Figure A1). A substantial proportion
183 of measurements, i.e. $> 75\%$, stem from various campaigns in Alaska (USA), followed
184 by Siberia (Russia). Measurements from European countries contribute $\approx$ five % of
185 the total dataset. Although the proportion on the total dataset is comparably low,
186 the research sites are spatially distributed across Europe, including Greenland and
187 Svalbard (Norway) (Figure A1).

188 The dataset comprised 31,647 spectral records collected across a range of mea-
189 surement conditions and instrument configurations. The majority of records were
190 acquired from canopy-level targets (87.6%), with leaf-level measurements representing
191 a smaller but notable proportion (5.9%); surface, twig, litter, bark, and flower targets
192 collectively accounted for less than 2.5% of records. Target metadata were absent for
193 4.3% of records. Regarding vegetation status, most reflectance spectra were collected
194 from live vegetation (85.8%), followed by fresh (i.e., recently harvested or moisture-
195 assessed) material (10.4%). Senescent, dead, dry, and degraded tissue states together
196 represented less than 1% of records, while vegetation status metadata were missing for
197 1.9% of records. Thirteen distinct field spectroradiometers were employed across con-
198 tributing datasets, with the UniSpec DC (36.9%), GER1500 (19.2%), and HR-1024i
199 (17.2%) accounting for the majority of measurements. ASD FieldSpec instruments in
200 various configurations contributed a further 7.2% of records collectively. The remain-
201 ing instruments, including the SR-2500, PSR+3500, UniSpec SC, and Specim IQ, each
202 accounted for less than 9% of records individually.

203 2.1.1 Species Inventory

204 Complete taxonomic information at the family, genus, and species level was avail-
205 able for 5,739 records (18 % of the full dataset), which formed the basis of the
206 species inventory (Table A1 and Figure 3). The species inventory comprised 216 taxa
207 across 57 families and 108 genera, representing three major functional groups: vas-
208 cular plants ($n = 27$ families, 57 genera, 113 species), lichens ($n = 20$ families, 41
209 genera, 77 species), and bryophytes ($n = 13$ families, 19 genera, 42 species). Vascular
210 plants constituted the most species-rich group, dominated by Salicaceae (16 species),
211 Ericaceae (16 species), and Poaceae (11 species), reflecting the characteristic domi-
212 nance of shrubs, dwarf shrubs, and grasses in arctic tundra vegetation. Within lichens,
213 Parmeliaceae (26 species) and Cladoniaceae (19 species) together accounted for 56 %
214 of lichen diversity, consistent with the prominence of foliose and fruticose growth forms
215 in high-latitude ecosystems. Bryophyte diversity was concentrated in Sphagnaceae
216 (16 species), Polytrichaceae (5 species), and Dicranaceae (4 species), underscoring
217 the ecological importance of *Sphagnum*-dominated communities in moisture-retaining
218 microhabitats characteristic of arctic tundra.

219 2.1.2 PCA and PERMANOVA

220 In both PCAs (Vis-NIR and Vis-SWIR), the first two principal components were suffi-
221 cient to explain $> 90\%$ of total spectral variance (PCA 1: $PC1 = 75.5\%$, $PC2 : 21.0\%$,

PCA 2: $PC1 = 75.7\%$, $PC2 : 16.0\%$, Figure 4), indicating a highly compact low-dimensional structure characteristic of vegetation reflectance spectra. $PC1$ captures overall reflectance magnitude and the contrast between VIS absorption and NIR reflectance across the red edge (≈ 700 nm, Figure 4). In the second PCA (Vis-SWIR), $PC2$ contrasts the NIR plateau against SWIR reflectance, reflecting a gradient in vegetation water content, while $PC3$ captures pigment-specific absorption in the VIS, with prominent features corresponding to chlorophyll a and b absorption bands (≈ 450 nm, ≈ 680 nm) and lignin- and cellulose-related absorption in the SWIR (> 2000 nm).

PERMANOVA on standardized $PC1$ – $PC2$ scores revealed significant effects of both biological and acquisition-related variables on spectral variance, though with markedly different effect sizes (Table 1). Among biological variables, vegetation status explained a greater proportion of spectral variance ($R^2 = 0.064$) than measurement target ($R^2 = 0.031$), with both terms significant ($p = 0.01$). Together, biological variables accounted for 9.5% of total spectral variance, with 82.8% remaining unexplained within groups. Among acquisition-related variables, dataset subset was by far the strongest predictor of spectral variance ($R^2 = 0.374$, $p = 0.01$), exceeding the combined explanatory power of all biological variables by a factor of approximately four. Geographic region contributed a small but statistically significant proportion of variance ($R^2 = 0.001$, $p < 0.05$), while instrument identity showed no independent effect on spectral variance ($R^2 < 0.001$, $p = 1.00$), suggesting that cross-instrument differences were negligible after data harmonization. Acquisition-related variables collectively explained 37.4% of spectral variance, with 51.3% attributed to residual within-group variation.

Table 1 Results of permutational multivariate analysis of variance (PERMANOVA; *adonis2*, 999 permutations, Euclidean distance) on standardized PC scores ($PC1$ – $PC2$, VIS–NIR PCA) of a stratified subsample of the Arctic tundra spectral library ($n = 3,667$ spectra). Biological variables (measurement target, vegetation status) and acquisition-related variables (instrument, dataset subset, geographic region) were tested in separate models with marginal effects (*by* = "margin"). R^2 values indicate the proportion of total spectral variance explained by each term.

Model	Term	<i>df</i>	R^2	<i>F</i>	
Biological variables	Measurement target	5	0.0314	23.54	$p = 0.01$
	Vegetation status	9	0.0638	26.58	$p = 0.01$
	Residual	3107	0.8283		
Acquisition variables	Instrument	1	0.0000	0.00	$p = 1.00$
	Dataset subset	86	0.3737	25.58	$p = 0.01$
	Geographic region	1	0.0007	4.40	$p < 0.05$
	Residual	3018	0.5126		

Despite the statistical significance, centroids of all factor groups were broadly distributed across the PC space without forming discrete clusters (Figure 5), consistent with the low R^2 values obtained from PERMANOVA and indicative of continuous, multifactorial spectral variation. The most strongly separated centroids along $PC2$ corresponded to flower reflectance spectra (measurement target; $PC2 = -1.68$), the GER1500 instrument ($PC2 = -2.08$), and dry vegetation status ($PC2 = -1.18$),

250 suggesting that this axis captures variation associated with desiccation and specific
251 spectral response characteristics of individual instruments. In contrast, PC1 was not
252 clearly associated with any single metadata variable.

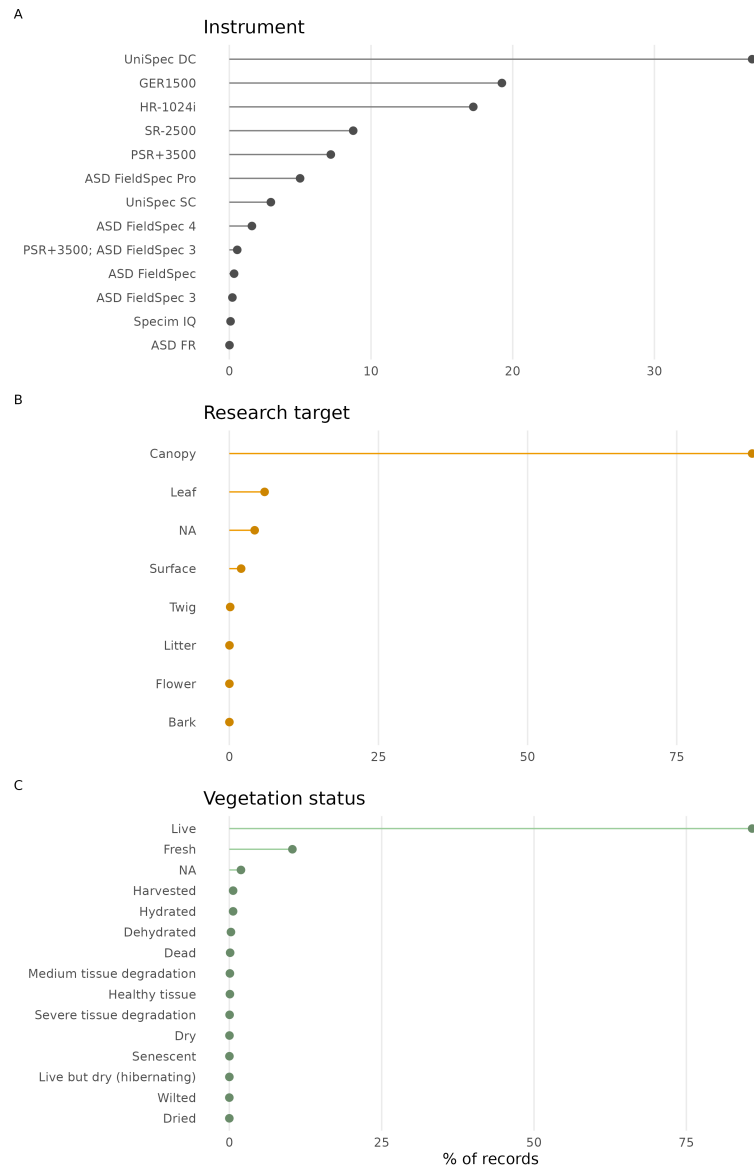


Fig. 2 Distribution of spectral records across key metadata variables: (A) instrument, (B) research target, and (C) vegetation status. Values represent the percentage of total records ($n = 31,647$). Vegetation status entries originally classified under moisture assessment protocols were reassigned to the "Fresh" category prior to analysis. Missing metadata are shown as "NA".

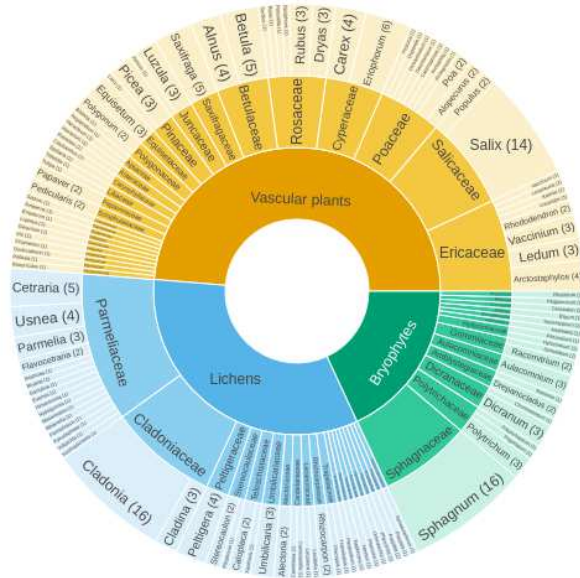
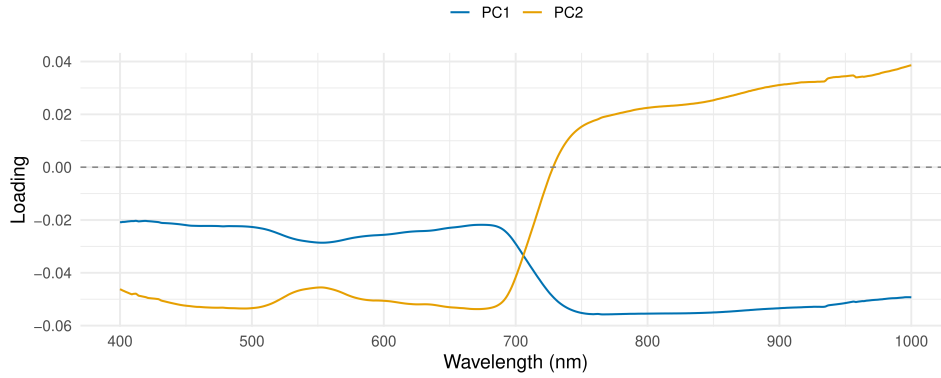


Fig. 3 Sunburst diagram illustrating the taxonomic composition of the species represented in the current version of the spectral library ($n = 5,739$ records that included the relevant taxonomic information), organized into three functional groups: vascular plants, bryophytes, and lichens (inner ring). The second ring shows families, and the outer ring shows genera with the number of recorded species in parentheses. Segment size is proportional to species richness. A summarising table can be found in the appendix (Table A1). An interactive version of the diagram was created using the *plotly*-package in R [25] and can be accessed here: [Figure 3 online](#).

A All instruments: Vis-NIR (400 nm - 1000 nm)

PC1: 75.57%, PC2: 20.9% | n = 23834 reflectance spectra



B Vis-SWIR instruments (400 nm - 2500 nm)

PC1: 75.74%, PC2: 16.08%, PC3: 3.46% | n = 6453 reflectance spectra

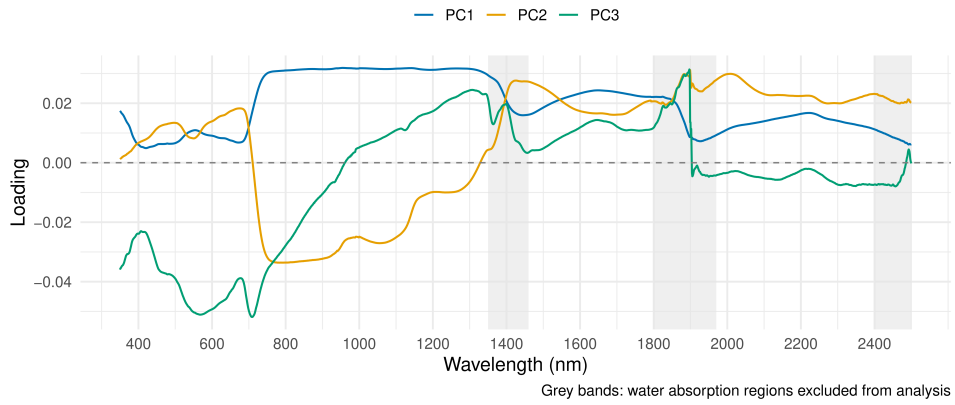


Fig. 4 PCA loadings of the Arctic tundra spectral library. (A) Loadings of the first two principal components (PC1: 75.57%, PC2: 20.9%) derived from a PCA of all instruments across the Vis-NIR range (400–1000 nm; n = 23,834 reflectance spectra). (B) Loadings of the first three principal components (PC1: 75.74%, PC2: 16.08%, PC3: 3.46%) derived from a PCA restricted to broadband instruments covering the full Vis-SWIR range (400–2500 nm; n = 6453 reflectance spectra). Grey shaded regions indicate atmospheric water absorption bands excluded from analysis.

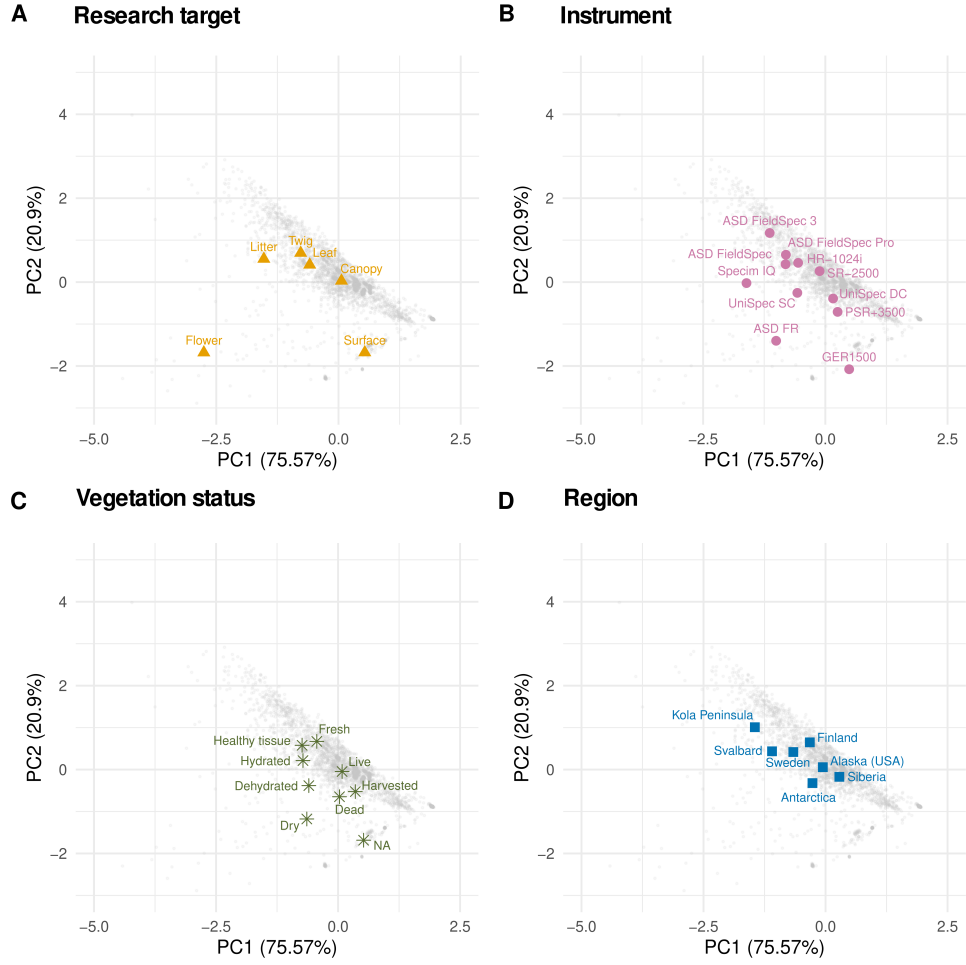


Fig. 5 Principal component analysis biplot of the Arctic tundra spectral library. Scores of a stratified subsample of reflectance spectra ($n = 3,667$) along the first two principal components (PC1: 75.5 %, PC2: 21.0%) are shown as grey points. Centroids of factor group levels derived from vector fitting (envfit, 999 permutations) are overlaid for measurement target (triangles), instrument (circles), vegetation status (stars), and geographic region (squares). All four variables were significantly associated with the PC space ($p < 0.001$; goodness-of-fit $R^2 = 0.046 - 0.140$). The broad distribution of centroids across the PC space without discrete clustering reflects the continuous, multifactorial nature of spectral variability in the database.

3 Discussion

A first class of challenges arose before any data could be examined: simply locating and deduplicating available datasets. Several datasets were distributed across multiple platforms under different titles, with no cross-referencing between them. Undetected duplication of this kind directly biases a spectral library by overrepresenting certain sites, species, or campaigns. This problem is particularly insidious because it is invisible in the final dataset without prior knowledge of the source material. Discoverability is further hampered by the absence of standardised, machine-readable metadata at the repository level, which prevents automated search and deduplication and forces time-intensive manual curation.

The most consequential challenge, however, was the fragmentation and internal inconsistency of dataset documentation. In the ideal case, all information necessary to interpret a spectral dataset, i.e. measurement protocol, instrument settings, preprocessing steps, and sample descriptions, is contained in a single, comprehensive data description document published alongside the data. In practice, essential metadata were frequently scattered across the dataset file itself, the repository landing page, a separate data description, and one or more associated research articles, requiring cross-referencing across sources to reconstruct a complete picture. More problematic were cases in which information from different sources was contradictory. In one instance, the data description stated that only hydrated samples had been measured, while the dataset itself gave no hydration information except for a single entry labelled "dried" in the notes column. Inconsistencies of this kind cannot always be resolved and introduce irreducible uncertainty into the harmonised product.

Harmonisation of file formats and data structures posed practical but generally tractable difficulties. The conventional CSV structure with one row per record and one column per wavelength or descriptive parameter is well understood and widely adopted, but many datasets deviated from it in ways that required manual intervention: transposed axes, long-format tables, mixed metadata rows inserted between data rows, or proprietary binary formats without accompanying reader software. Advanced formats such as HDR are better suited to large hyperspectral datasets and are likely to become increasingly important as data volumes grow. The most time-intensive cases involved structurally malformed files, where metadata columns had been transposed into rows and interspersed irregularly with data records, necessitating row-by-row manual correction.

Geospatial and temporal metadata were inconsistently reported across nearly all sources. Exact measurement coordinates were frequently absent, replaced by general site coordinates or, in some cases, only a site name. In remote regions with few formally registered place names, or where common names recur across a large area (such as "Eagle Creek" in Alaska) rendered measurement locations unidentifiable. Reliable timestamp information was available for only 5,104 of 31,647 reflectance spectra (16.1%) after conversion to UTC. For the remaining reflectance spectra, time-zone information was either absent or flagged as unreliable, hampering consistent cross-dataset time harmonization. Consequently, the potential influence of measurement time and season on spectral variability could not be systematically assessed. Among reflectance spectra with valid timestamps, recordings were concentrated in

June through August, reflecting the typical Arctic field season, with no representation of other seasons sufficient for a meaningful phenological analysis. Diurnal effects on reflectance mediated through solar elevation angle and diffuse-to-direct radiation ratio therefore remain an unquantified source of variability in the present database. However, this parameter should be considered in future data collection efforts through systematic recording of acquisition time and timezone in a standardised format.

Where times were recorded, inconsistent use of 12- and 24-hour formats, ambiguous or incorrect time zone specifications, and imprecise date ranges (e.g. "austral summer 2018" or "end of January 2018") complicated or prevented reliable temporal harmonisation.

The greatest harmonisation effort was required for research object descriptions which contain the textual labels that identify what was measured. These ranged from precise binomial species names to vague community descriptions, surface type labels, and in one case, photographs with no accompanying text, requiring manual image interpretation. A recurring problem was the use of self-defined, undocumented abbreviations for species names: abbreviations such as "carpra" or "sapu" are ambiguous across multiple taxa (*Cardamine pratensis* or *Carex prasina*; *Salix pulchra* or *Saxifraga punctata*) and could not be resolved unambiguously without external confirmation. Equally problematic was the mixing of measurements at fundamentally different levels of biological organisation, such as individual leaves, whole canopies, mixed communities, and bare surfaces within a single descriptive column, without an explicit indicator of measurement target. For machine learning applications, where training labels must be consistent and unambiguous, this lack of hierarchical, standardised classification is a critical limitation: it forces manual re-labelling that is both labour-intensive and introduces subjective decisions into the training data.

Finally, heterogeneous data processing constituted a structural challenge that cannot be fully resolved in post-hoc harmonisation. Raw data are unambiguous and maximally flexible; preprocessed data carry embedded assumptions about smoothing, interpolation, and averaging that are difficult or impossible to reverse and that vary in ways that affect downstream model behaviour. Many datasets in the library had already undergone processing to varying degrees and with varying levels of documentation, making it impossible to achieve a fully standardised processing baseline across the full dataset. The reporting of reflectance values compounded this: without explicit specification of whether values are given as decimal fractions or percentages, datasets containing values exceeding 1.0 are ambiguous and it remains unclear whether such values represent valid percentage-scale reflectances or measurement errors.

The spatial distribution of sampling sites compiled in the harmonised dataset reveals a pronounced geographic bias that is unlikely to reflect the true ecological diversity of the Arctic (Fig. 1). Siberia and Canada are markedly underrepresented relative to their share of circumpolar landmass, while Alaska contributes a disproportionately large number of reflectance spectra despite its comparatively small areal extent. This imbalance is not primarily an ecological sampling problem, it rather is a data access problem. It reflects the heterogeneous structure of existing archives, compounded by differences in language, data-sharing culture, and open-data infrastructure across national research communities. That a dataset assembled from over

two decades of field campaigns across the circumpolar Arctic should be so geographically skewed is, in itself, a diagnostic finding: it points to systemic fragmentation in how spectroscopic data are collected, stored, and shared within the community. The approximately 600 working hours required to compile, evaluate, and harmonise the 111 datasets underlying this library make those hidden costs tangible. The challenges we encountered in the process are therefore not incidental but they are characteristic of the current state of field spectroscopy data in ecological remote sensing, and we discuss them here as a community-level issue rather than a dataset-specific one.

The spectral variability structure of the assembled Arctic tundra spectral library reflects the complex interplay of biological, ecological, and methodological factors inherent to multi-source field spectroscopy databases. The finding that only two principal components were sufficient to explain 96.4% of total spectral variance is consistent with the well-established low intrinsic dimensionality of vegetation reflectance spectra [26], especially when considering leaf-level reflectance spectra or those of low dimensional canopies. They are largely influenced by a small number of co-varying biochemical and structural properties such as chlorophyll content, leaf water content, and canopy architecture [27]. This compact variance structure suggests that, despite the heterogeneous origin of the reflectance spectra, the database captures a coherent continuum of Arctic tundra optical properties rather than a collection of spectrally incompatible measurements. The modest but statistically significant contributions of measurement target ($R^2 = 0.033$) and vegetation status ($R^2 = 0.049$) to spectral variance confirm that biologically meaningful signal is preserved across the database. The separation of flower and litter reflectance spectra from canopy measurements along PC2, and the systematic displacement of dry and dehydrated vegetation status centroids, are consistent with known spectral effects of pigment composition, water content, and structural organization [28, 29]. These findings validate the potential of the database for trait-oriented analyses. Further, they underline the importance of stratifying by measurement target and vegetation status in downstream applications to avoid a confusion of biological gradients and sampling artefacts. The surprising absence of an independent instrument effect ($R^2 < 0.001$) is of particular interest, as it suggests that cross-instrument spectral differences are not a primary driver of variance in the harmonized dataset. However, this result should be interpreted with caution as the dataset underwent several pre-processing and data cleaning steps in order to be in a operational shape. Further, the envfit-based centroids revealed systematic displacement of specific instruments along PC2, most prominently the GER1500 ($PC2 = -2.08$) and ASD FR ($PC2 = -1.40$). This results indicates that instrument-specific spectral response characteristics do influence spectral positioning within the PC space even if their marginal contribution to total variance as estimated by PERMANOVA is negligible.

Disentangling instrument-induced bias from genuine ecological signal remains a methodological challenge in multi-source spectral databases. As a solution, continuing harmonization efforts might consider explicit cross-instrument calibration or transfer function approaches.

The strongest single predictor of spectral variance was dataset subset ($R^2 = 0.300$). They represent individual measurement campaigns rather than a coherent ecological

388 or methodological variable. This finding most likely reflects the compounded influence
389 of various campaign-specific factors, including differences in target species composi-
390 tion, phenological timing of measurements, local meteorological conditions, observer
391 protocols, and preprocessing workflows.

392 The magnitude of this effect highlights a fundamental challenge in assembling
393 multi-source spectral libraries: campaign identity captures a broad mixture of ecolog-
394 ical and methodological variance that cannot easily be decomposed without detailed
395 campaign-level metadata.

396 The weak geographic signal ($R^2 = 0.001$, $p = 0.08$) may appear surprising given
397 the broad spatial extent of the database, spanning regions from Alaska and Svalbard
398 to Siberia and Antarctica. However, this finding is consistent with the observation that
399 Arctic tundra plant functional types share broadly similar spectral properties across
400 regions, with within-site variation often exceeding between-region differences. It may
401 also reflect the uneven geographic sampling of the database, with Alaska contribut-
402 ing the majority of reflectance spectra, potentially suppressing detectable regional
403 gradients.

404 The challenges described above are not unique to Arctic tundra spectroscopy, nor
405 to this dataset. They are structural features of a research culture in which data sharing
406 has been, until recently, an afterthought rather than an integral part of the scientific
407 workflow. The rapid expansion of hyperspectral EO capacity with operational missions
408 such as EnMAP already generating global data streams and CHIME set to follow is
409 transforming the stakes of this issue. Machine learning models capable of retrieving
410 plant functional traits from satellite imagery at continental scale are within reach, but
411 their ecological validity depends entirely on the quality, diversity, and interoperability
412 of the field spectroscopy datasets used to train and validate them. A spectral library
413 assembled from poorly documented, inconsistently labelled, and heterogeneously pre-
414 processed data will produce models that are difficult to interpret, hard to validate,
415 and unlikely to generalise reliably across biomes or sensor configurations.

416 The transition required is neither technically complex nor resource-intensive. It is
417 primarily a shift in norms. Adopting consistent coordinate reporting, structured and
418 hierarchical target descriptions, raw data publication, and comprehensive standalone
419 data descriptions costs little at the point of data collection but yields compounding
420 returns as datasets are reused, integrated, and built upon by the community. The FAIR
421 principles (Findable, Accessible, Interoperable, Reusable) provide a well-established
422 framework for this transition [30]; what the spectroscopy community needs is their
423 concrete translation into discipline-specific practice. The checklist we provide in the
424 Conclusions section is intended as a practical first step in that direction. Not a compre-
425 hensive standard, but a set of minimum expectations that, if adopted broadly, would
426 substantially reduce the friction of future harmonisation efforts and strengthen the
427 ecological credibility of hyperspectral machine learning at scale.

428 4 Conclusion

429 Based on our experiences of data collection and harmonisation, we propose the follow-
430 ing recommendations to increase the reusability of the data and enhance its potential

431 for implementation in for ecological applications, such as machine learning models.
432 A checklist for personal use is provided in the Supplementary Material. In addition,
433 we provide a living document open for suggestions from the community on GitHub
434 ([Spec-Lib-Wiki](#)).

435 **Distribution**

- 436 • Provide each dataset in a single primary repository. If distribution across multiple
437 platforms is necessary, use the identical title on all platforms and clearly cross-
438 reference the alternative distribution locations.
- 439 • Publish related datasets as a coherent data series with a common citation, rather
440 than as multiple independent single datasets.
- 441 • Explicitly state the recommended citation format for the dataset.
- 442 • Whenever possible, publish raw data. Preprocessed data may be provided addition-
443 ally, but should not replace the raw data.

444 **Documentation**

- 445 • In addition to the dataset itself, publish a comprehensive data description document
446 that contains all information relevant to the dataset.
- 447 • The data description should provide detailed documentation of all technical aspects
448 of the measurement campaign, including environment, light source, instrument,
449 measurement setup, and, where applicable, preprocessing procedures. All descrip-
450 tive parameters included in the dataset should be clearly explained and their units
451 be specified.
- 452 • In the data description, explicitly highlight the presence of a substantial number of
453 erroneous or invalid values, if applicable, and briefly discuss potential causes.
- 454 • No information relevant to the published dataset should appear exclusively on the
455 distribution platform or in associated research articles without also being included
456 in the data description document.
- 457 • Generalized statements in the data description and on the distribution platform
458 must apply to every sample in the dataset.
- 459 • Preferably choose a distribution platform that requires only minimal generalized
460 metadata and allows for detailed dataset-specific documentation.

461 **File Formats and Data Structures**

- 462 • Provide the dataset in CSV format, optionally in addition to more advanced file
463 formats.
- 464 • In the CSV file, use the following structure: each record represented by one row,
465 and each descriptive parameter and wavelength represented by one column.
- 466 • Carefully check the dataset for formatting errors prior to publication.
- 467 • Within a data series, consistently use the same structure, identical column names,
468 and consistent units across all datasets.

469 Descriptive Parameters

- 470 • Always provide the geographic coordinates of the measurement location for field
471 measurements and of the sampling location for laboratory measurements. Coordi-
472 nates are more important than the site name. Decimal degrees are recommended.
- 473 • Provide the date (day-level precision) of the measurement. For laboratory measure-
474 ments, additionally provide the date of sample collection.
- 475 • Provide the time of measurement for field measurements. The 24-hour clock format
476 (HH:MM) is recommended; seconds are not required.
- 477 • Always use local time and clearly specify the corresponding time zone.
- 478 • Use research object descriptions that are as consistent as possible and provide classi-
479 fications at different levels: In addition to a precise (yet as standardized as possible)
480 research object description, include a separate column indicating whether the object
481 represents vegetation, water, ground material, or mixed reflectance spectra thereof.
482 Add further columns for lower-level classifications where appropriate (e.g., division
483 or growth habit for individual species).
- 484 • Use a dedicated column to specify the species. Provide full species names or unam-
485 biguous abbreviations from official systems (e.g., the USDA Plant Database). Do
486 not use self-defined abbreviations in the officially published version of the dataset.
- 487 • Always specify the measurement target, particularly for measurements of individual
488 species.
- 489 • Do not include information in the notes column that applies to every measurement.
490 Instead, create dedicated columns for such information. Vegetation status (e.g., live,
491 dead, decayed, moisture content) and light conditions (depending on the light source:
492 lamp type or cloud cover) should be reported for each measurement in separate
493 columns.
- 494 • Indicate whether the measurement was conducted in the field or in the laboratory.
- 495 • In the descriptive parameters, include only information that is comprehensible to
496 external users. Do not use internal project-specific identifiers (e.g., plot numbers or
497 abbreviations) unless they are explicitly explained in the data description.

498 Technical Information

- 499 • Specify which measurement instrument was used.
- 500 • Indicate whether the data are raw or processed.
- 501 • State how many individual measurements were averaged to obtain one record.
502 Explicitly indicate if no averaging was performed to ensure that this information
503 was not omitted unintentionally.
- 504 • In addition to providing a detailed documentation of all preprocessing procedures
505 in the data description, indicate in the dataset itself in a short version for each
506 record whether the respective preprocessing procedures were applied: averaging,
507 interpolation, smoothing, and trimming.
- 508 • Specify the unit in which reflectance values are reported (decimal or percentage).

5 Methods

Search Criteria

The presented spectral library integrates hyperspectral reflectance data from Arctic tundra ecosystems, with a special focus on moss and lichen measurements. Data were considered hyperspectral if they covered at least 400 to 1000 nm in contiguous narrow bands (< 10 nm FWHM), consistent with Goetz [31], Goetz et al. [32] and commonly applied in vegetation remote sensing. We only included data from field and lab spectroscopy (as described in the introduction) and excluded UAV and satellite-based remote sensing data to generate a hyperspectral in-situ reference database. We considered reflectance spectra of vascular plants, mosses, lichens, algae and mixed canopies from Arctic tundra ecosystems as well as additional reflectance spectra from Antarctica. Leaf, flower and canopy reflectance spectra of single plant species and species mixtures were included. We also accepted reflectance spectra of different non-vegetated surfaces in the Arctic and Antarctic tundra, e.g. water and ground material like bare soil, roads, gravel and rocks, but rejected datasets with a focus on ice sheets and sea ice and those explicitly targeted on Arctic geology and minerals. The vegetation samples were allowed to be in different states during the measurements, e.g. live, dead, hydrated and dehydrated. However, we did not take into account pulverized samples for either vegetation or soil.

We considered Level-0 as well as Level-1 data, but preferred the former if both versions were provided. Level-0 data was defined as reflectance data before filtering, smoothing or any post-processing was applied. All data that had been subject to further processing steps was considered Level-1 data. Overall, we have gathered 111 datasets from 74 sources, containing a total of 31,647 reflectance spectra measured between 1999 and 2023. A list of these datasets is shown in table 3 (Appendix). However, we acknowledge the fact that our library does not represent a complete collection of all the available data that meets the search criteria.

Data harmonization

To this day, most hyperspectral data are provided in CSV format with each column representing a wavelength range and each row representing a spectrum. Although increasingly more advanced data formats are being used to store hyperspectral data, we have opted for this format and structure for the time being. Therefore, data provided in formats other than CSV (e.g., TAB, HDF5, HDR) or with different structures was converted to CSV and restructured to match the described structure in the first place. In the second place, we defined a set of descriptive parameters to be adopted for the harmonized spectral library. The individual datasets contained information on different metadata, depending on the purpose for which the data had originally been collected. Based on this pool of information, we defined five key aspects of a measurement that must be specified: i) geographical position, ii) time (time of day and date), iii) research object, iv) condition of the research object and the measurement environment, and v) technical information about the measuring instrument and data

preprocessing. The accuracy of the metadata in the original datasets varied significantly. In some cases, the metadata was directly assigned to the individual records, while in others, only information on the general measurement conditions of an entire measurement campaign was provided in related publications and data description documents or on the distribution platform. We aimed to preserve as much and as accurate information as possible while editing the original metadata as little as possible. Nevertheless, the consistency of the entries had to be enhanced in order to be able to analyse the data usefully. Thus, instead of reducing accuracy in favour of consistency, we have rather added further descriptive parameters that either specify the accuracy of other parameters or extract key information from other parameters and provide them in a more applicable way. This procedure can be illustrated with two examples: Geolocation is described by five parameters: site name, region, latitude, longitude, accuracy level. The region parameter allows to group records by their geolocation. Latitude and longitude contain the measurement coordinates in decimal degrees and enable spatial analyses. However, the coordinates were not always provided for each measurement individually, but sometimes only at the plot or site level. The accuracy level was described in various manners across the different data sources, e.g. “measurement coordinates”, “plot centre coordinates” (including an information about the plot size) and “site centre coordinates” (including an indication of whether the coordinates were specified by the authors themselves or derived from the site name).

The research object is described by seven parameters. One is an exact replicate of the code, term or phrase used as a research object description in the original dataset and, thus, preserves its full accuracy. In order to enable data grouping at different levels, we added five additional parameters whose categorized entries are derived from the original description: the type comprises the categories “vegetation”, “water”, and “ground” and combinations of them. The specification additionally categorizes vegetation samples of single plant species by their division and growth form (e.g. “moss”, “lichen”, “graminoid”, “shrub”) and contains a simpler version of the research object description for records of mixed canopies or non-vegetated surfaces. The family, genus and species are only indicated for single plant species records. We manually retrieved information about the division, growth form and family of plant species from the USDA Plant Database (<https://plants.usda.gov>) and the Global Biodiversity Information Facility (GBIF, <https://www.gbif.org>). Genus and species were also retrieved from the USDA Plant Database for records where the USDA Symbol was used as research object description. A seventh parameter specifies the target (i.e. the part of the research object) which is measured. It comprises the categories “leaf”, “flower”, “twig”, “bark”, “litter” and “canopy” for vegetation samples and “surface” for all other materials. This is the only parameter characterising the research object for which the information content has been reduced in order to achieve harmonized data.

In total, 24 descriptive parameters were included (see table 2). Beside those described above, categorization was also performed for the environment (“field”, “laboratory”) and light condition (“lamp” (or a specification of the lamp), “sunny”, “mostly sunny”, “partly cloudy”, “mostly cloudy”, “overcast”) parameters. Depending on the measuring instrument, the raw data usually had a spectral resolution of 1 to 3 nm. To harmonize them, we interpolated all records with resolutions coarser than 1 nm to

Table 2 Set of 24 descriptive parameters that were used for the harmonisation of the 31,600+ measurements from different hyperspectral campaigns into a single spectral library.

Key aspect	Descriptive parameter	Examples
Geolocation	site, region, latitude, longitude, accuracy level of coordinates	Atqasuk, Alaska, (70.5, -157.0), "Measurement coordinates"
Time	recording date, recording time, time zone	2017-06-29, 14:40, AKDT
Research object	research object description, type, specification, family, genus, species, target	vegetation, Arctic tundra, canopy
Conditions	vegetation status, environment, light conditions, notes	"live"
Technical information	instrument, manufacturer, number of samples per record, preprocessing original dataset, preprocessing during harmonisation	Unispec DC, raw data

1 nm and converted reflectances given as percentages into decimal numbers. Records containing measured values outside the wavelength range of 350 to 2500 nm were trimmed to this range, and records with less data were filled with NA. We did not consider the type of physical reflectance.

Analysis of the spectral dataset

We used R version 4.5.2 in R Studio [33] to perform the statistical analysis of the hyperspectral dataset. Prior to analysis, spectral reflectance values were screened and corrected for several data quality issues identified across instrument-subset combinations. Fill values (-9999 , Inf) were set to NA. Reflectance spectra recorded in percent reflectance units (subsets 25, 32, 37, 50; UniSpec DC) were converted to fractional reflectance by division by 100. Four subsets (subsets 27, 99, 100, 103) were excluded entirely due to irreconcilable unit inconsistencies, retaining 29,316 reflectance spectra for further analysis. Small negative reflectance values likely arising from instrument noise ($-0.1 < r < 0$) were clipped to zero, while values below -0.1 were set to NA as physically implausible. An upper reflectance threshold of 1.2 was applied, above which values were treated as NA, as reflectance values exceeding this threshold are not plausible for Arctic tundra vegetation under field conditions. To assess spectral variability across the full optical range covered by the database, two complementary PCAs were performed. The first PCA included all instruments and was restricted to the visible and near-infrared range (Vis-NIR; 400–1000 nm), as narrowband instruments (UniSpec DC, GER1500, UniSpec SC, $n = 23,834$ reflectance spectra after quality filtering) do

not cover the shortwave infrared (SWIR) and would have introduced excessive missing
 data beyond 1000 nm. The second PCA was restricted to instruments covering the full
 Vis-SWIR range (ASD FieldSpec, ASD FieldSpec 3, ASD FieldSpec 4, ASD FieldSpec
 Pro, ASD FR, HR-1024i, PSR+3500, SR-2500; $n = 6453$ reflectance spectra after qual-
 ity filtering), allowing loadings to be interpreted across the full 400–2500 nm range.
 Prior to the Vis-SWIR PCA, spectral bands within known atmospheric water absorp-
 tion regions (≈ 1350 – 1460 nm, ≈ 1800 – 1970 nm, ≈ 2400 – 2500 nm) were excluded
 where the fraction of missing values exceeded 50 % of broadband spectra. Remaining
 reflectance spectra with any missing values after band filtering were excluded from
 both PCAs. Both PCAs were performed on mean-centred, unscaled reflectance matri-
 ces using *prcomp* in R. As the strict data filtering for the Vis-SWIR PCA resulted in
 significant loss of input data, the following analysis were performed considering the
 Vis-NIR region of the reflectance spectra. Two principal components were sufficient to
 explain 96.4 % of the total spectral variance across all instruments (PC1: 75.5 %, PC2:
 21.0 %, Figure A2), indicating that the dominant axes of variation in the dataset are
 captured by a highly compact low-dimensional structure. To quantify the contribu-
 tion of metadata variables to spectral variance, a permutational multivariate analysis
 of variance (*PERMANOVA*; *adonis2*, *vegan-package*) was performed on the PC1–PC2
 scores using Euclidean distance. Variables tested included measurement target, vege-
 tation status, instrument, geographic region, and dataset subset. Each term was tested
 marginally (by = "margin") to obtain independent estimates of explained variance
 (R^2) regardless of term order. Prior to *PERMANOVA*, PC-scores were standardized
 to unit variance to ensure equal weighting of both axes. A stratified subsample of the
 data was drawn proportionally across instrument–subset combinations (minimum 30
 reflectance spectra per stratum) to reduce computational load while maintaining rep-
 resentation of all groups. *PERMANOVA* p-values were based on 999 permutations. To
 further assess whether spectral dispersion differed systematically between instrument
 groups, which could be indicative of a measurement bias, a multivariate homogeneity
 of variance test was conducted using the *betadisper* followed by a permutation test
 (*permutest*, 999 permutations).

647 5.1 List of datasets

Table 3: List of data sources integrated in the harmonized dataset. The number of datasets per publication as well as the number of records are included to represent the contribution of single sources to the total dataset. In some cases, the authors explicitly expressed the wish to have the dataset cited alongside the respective manuscript. No matter the number of records, we highly appreciate the work behind every single dataset. For the record, two datasets from Antarctica are named in the list (marked with *) as they were found alongside Arctic data sources and should be made available. Although integrated in the final dataset to be ready to use, they were not included in the here presented analyses.

Reference	Title	No. of data sets	No. of records	URL
Beamish [34], supplementary data to Beamish et al. [35]	Plot level spectroscopy measurements of low-Arctic vegetation, Toolik Research Station and Innvait Vegetation Grid, Toolik Lake, Alaska	2	6079	https://doi.pangaea.de/10.1594/PANGAEA.885801
Buchhorn et al. [36]	hyDRaCAT Spectral Reflectance Library: Hyperspectral Field Spectroscopy and Field Spectro-Goniometry of Siberian and Alaskan Tundra	1	9	https://doi.pangaea.de/10.1594/PANGAEA.855997
* Chi and Lee [37], supplementary data to Chi et al. [38]	Field spectra of 17 vegetation species from 400 to 2500 nm in Barton Peninsula	1	17	https://kpd.c.kopri.re.kr/search/4f6a8845-4929-4029-98c9-1dd592274016
Supplementary data to Davidson et al. [39]	[data not published]	1	402	-
Halbritter et al. [40], described in Vandvik et al. [41]	PFTC4 - PFTCourses, Elevational Gradient, Bird Cliff and ITEX Experiment, Longyearbyen, Svalbard	1	470	https://osf.io/smbqh/overview
Huemmrich and Campbell [42]	Tundra Plant Leaf-level Spectral Reflectance and Chlorophyll Fluorescence, 2019-2021	1	107	https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=2005
Huemmrich and Gamon [43]	Tundra Plant Reflectance, CO2 Exchange, PAM Fluorometry, and Pigments, AK, 2001-2002	1	928	https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1960
Huemmrich and Gamon [44]	Spectral Reflectance and Ancillary Data, Tundra Transect, North Slope, AK, 2000-2022	4	9615	https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=2232
Kokaly et al. [45]	USGS Spectral Library Version 7	1	4	https://www.sciencebase.gov/catalog/item/5807a2a2e4b0841e59e3a18d
Supplementary data to Nelson et al. [46]	Laboratory of Ecological Spectroscopy (lecospec)	1	1925	https://github.com/nelsopet/lecospec/tree/dev/Output
Rees et al. [47]	Spectral Library of Arctic Plants	1	354	https://www.repository.cam.ac.uk/items/680cdb10-f5c6-4a0f-b6e5-03c659afc88d
Rich and Csatho [48], supplementary data to Rich and Trochim [49]	Spectral Radiometer Data for the North Slope, Alaska	1	23	https://rsl.geology.buffalo.edu/data/Pages/NorthSlope_Data.html
Runge et al. [50]	Hyperspectral field spectrometry of Arctic vegetation units in the central Lena Delta	28	2767	https://doi.pangaea.de/10.1594/PANGAEA.945982
Salko et al. [51], supplementary data to Salko et al. [52]	Geographically extensive spectral library of peatland vegetation from 13 hemiboreal, boreal, sub-Arctic and Arctic peatland sites	1	128	https://data.mendeley.com/datasets/3866tj3w8v/2
Salko et al. [53], supplementary data to Salko et al. [54]	Reflectance spectra of nine boreal Sphagnum moss species	1	360	https://data.mendeley.com/datasets/wm5fcxmdmzd/3
Serbin et al. [55]	NGEE Arctic HR1024i Canopy Spectral Reflectance, Drained Thaw Lake Basin, Barrow, Alaska, July 2015	1	58	https://ecosis.org/package/ngee-arctic-hr1024i-canopy-spectral-reflectance--drained-thaw-lake-basin--barrow--alaska--july-2015
Serbin et al. [56]	NGEE Arctic BNL Canopy Spectral Reflectance Utqiagvik (Barrow) Alaska 2014 to 2016	1	178	https://ecosis.org/package/ngee-arctic-bnl-canopy-spectral-reflectance-utqiagvik--barrow--alaska-2014-to-2016

Serbin et al. [57]	NGEE Arctic Leaf Spectral Reflectance and Transmittance Data 2014 to 2016 Utqiagvik (Barrow) Alaska	1	397	https://ecosis.org/package/ngee-arctic-leaf-spectral-reflectance-and-transmittance-data-2014-to-2016-utqiagvik--barrow--alaska
Serbin and Rogers [58]	NGEE Arctic 2016 Leaf Spectral Reflectance Kougatok Road Watershed Seward Peninsula Alaska	1	149	https://ecosis.org/package/ngee-arctic-2016-leaf-spectral-reflectance-kougatok-road-watershed-seward-peninsula-alaska
Serbin et al. [59]	NGEE Arctic 2016 Averaged Canopy Spectral Reflectance Seward Peninsula Alaska	1	43	https://ecosis.org/package/ngee-arctic-2016-averaged-canopy-spectral-reflectance-seward-peninsula-alaska
Serbin et al. [60]	NGEE Arctic Leaf Spectral Reflectance Utqiagvik (Barrow) Alaska 2013	1	69	https://ecosis.org/package/ngee-arctic-leaf-spectral-reflectance-utqiagvik--barrow--alaska-2013
Serbin et al. [61]	NGEE Arctic 2019 Canopy Spectral Reflectance Seward Peninsula Alaska	1	129	https://ecosis.org/package/ngee-arctic-2019-canopy-spectral-reflectance-seward-peninsula-alaska
Serbin et al. [62]	NGEE Arctic 2019 Leaf Spectral Reflectance Seward Peninsula Alaska	1	99	https://ecosis.org/package/ngee-arctic-2019-leaf-spectral-reflectance-seward-peninsula-alaska
Serbin et al. [63]	NGEE Arctic 2017 Canopy Spectral Reflectance Seward Peninsula Alaska	1	511	https://ecosis.org/package/ngee-arctic-2017-canopy-spectral-reflectance-seward-peninsula-alaska
Serbin et al. [64]	NGEE Arctic 2017 Leaf Spectral Reflectance Teller Watershed Seward Peninsula Alaska	1	163	https://ecosis.org/package/ngee-arctic-2017-leaf-spectral-reflectance-teller-watershed-seward-peninsula-alaska
Serbin et al. [65]	NGEE Arctic 2018 Canopy Spectral Reflectance Kougatok Road Watershed Seward Peninsula Alaska	1	22	https://ecosis.org/package/ngee-arctic-2018-canopy-spectral-reflectance-kougatok-road-watershed-seward-peninsula-alaska
Serbin et al. [66]	NGEE Arctic 2018 Transect Spectral Reflectance Seward Peninsula Alaska	1	285	https://ecosis.org/package/ngee-arctic-2018-transect-spectral-reflectance-seward-peninsula-alaska
Serbin et al. [67]	NGEE Arctic 2018 Vegetation Endmember Spectral Reflectance Kougatok Rd Seward Peninsula Alaska	1	95	https://ecosis.org/package/ngee-arctic-2018-vegetation-endmember-spectral-reflectance-kougatok-rd-seward-peninsula-alaska
Serbin et al. [68]	NGEE Arctic 2018 Vegetation Plot Spectral Reflectance Seward Peninsula Alaska	1	182	https://ecosis.org/package/ngee-arctic-2018-vegetation-plot-spectral-reflectance-seward-peninsula-alaska
Serbin et al. [69]	NGEE Arctic Select Non Vegetation Spectral Reflectance Seward Peninsula Alaska	1	36	https://ecosis.org/package/ngee-arctic-select-non-vegetation-spectral-reflectance-seward-peninsula-alaska
Unger et al. [70]	Arctic Moss Spectral Reflectance Desiccation Experiment From Samples Collected in Northern Alaska	1	48	https://ecosis.org/package/arctic-moss-spectral-reflectance-desiccation-experiment-from-samples-collected-in-northern-alaska
Van der Veen and Csatho [71], supplementary data to Van der Veen and Csatho [72]	Spectral Radiometer Data for West Greenland	1	480	https://rsl.geology.buffalo.edu/data/Pages/Jakobshavn.Data.html
Vargas-Zesati et al. [73]	2010-2017 Atkasuk, Alaska CALM Plots Canopy Reflectance Spectra (Uni)	1	870	https://ecosis.org/package/2010-2017-atkasuk--alaska-calm-plots-canopy-reflectance-spectra--uni
Vargas-Zesati et al. [74]	2017 Eagle Creek, Alaska Plant Species Leaf Reflectance Spectra (SVC)	1	90	https://ecosis.org/package/2017-eagle-creek--alaska-plant-species-leaf-reflectance-spectra--svc
Vargas-Zesati et al. [75]	2017 Imnavait, Alaska MISP Transect Canopy Reflectance Spectra (SVC)	1	46	https://ecosis.org/package/2017-imnavait--alaska-misp-transect-canopy-reflectance-spectra--svc

Vargas-Zesati et al. [76]	2017 No Name Creek, Alaska Plant Species Reflectance Spectra (SVC)	1	26	https://ecosis.org/package/2017-no-name-creek--alaska-plant-species-reflectance-spectra--svc-
Vargas-Zesati et al. [77]	2017 Sagwon, Alaska Ecotype Site Canopy Reflectance Spectra (SVC)	1	133	https://ecosis.org/package/2017-sagwon--alaska-ecotype-site-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [78]	2017 Sagwon, Alaska Ecotype Tussock Canopy Reflectance Spectra (SVC)	1	12	https://ecosis.org/package/2017-sagwon--alaska-ecotype-tussock-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [79]	2017 Sagwon, Alaska Plant Species Leaf Reflectance Spectra (SVC)	1	30	https://ecosis.org/package/2017-sagwon--alaska-plant-species-leaf-reflectance-spectra--svc-
Vargas-Zesati et al. [80]	2017 Toolik, Alaska Ecotype Site Canopy Reflectance Spectra (SVC)	1	17	https://ecosis.org/package/2017-toolik--alaska-ecotype-site-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [81]	2017 Toolik, Alaska MISP Transect Canopy Reflectance Spectra (SVC)	1	45	https://ecosis.org/package/2017-toolik--alaska-misp-transect-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [82]	2017 Toolik, Alaska Plant Species Leaf Reflectance Spectra (SVC)	1	82	https://ecosis.org/package/2017-toolik--alaska-plant-species-leaf-reflectance-spectra--svc-
Vargas-Zesati et al. [83]	2017 Utqiagvik, Alaska BEO Canopy Reflectance Spectra (SVC)	1	59	https://ecosis.org/package/2017-utqia-vik--alaska-beo-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [84]	2017 Utqiagvik, Alaska CALM Plots Canopy Reflectance Spectra (SVC)	1	60	https://ecosis.org/package/2017-utqia-vik--alaska-calm-plots-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [85]	2017 Utqiagvik, Alaska Coastal Survey Canopy Reflectance Spectra (SVC)	1	109	https://ecosis.org/package/2017-utqia-vik--alaska-coastal-survey-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [86]	2017 Utqiagvik, Alaska DEM Site Canopy Reflectance Spectra (SVC)	1	28	https://ecosis.org/package/2017-utqia-vik--alaska-dem-site-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [87]	2017 Utqiagvik, Alaska ITEX Grid Canopy Reflectance Spectra (SVC)	1	79	https://ecosis.org/package/2017-utqia-vik--alaska-itex-grid-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [88]	2017 Utqiagvik, Alaska Met Tower D Canopy Reflectance Spectra (SVC)	1	25	https://ecosis.org/package/2017-utqia-vik--alaska-met-tower-d-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [89]	2017 Utqiagvik, Alaska Microtopo Grid Canopy Reflectance Spectra (SVC)	1	136	https://ecosis.org/package/2017-utqia-vik--alaska-microtopo-grid-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [90]	2017 Utqiagvik, Alaska MISP Transect Canopy Reflectance Spectra (SVC)	1	636	https://ecosis.org/package/2017-utqia-vik--alaska-misp-transect-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [91]	2017 Utqiagvik, Alaska Mounds Sites Canopy Reflectance Spectra (SVC)	1	102	https://ecosis.org/package/2017-utqia-vik--alaska-mounds-sites-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [92]	2017 Utqiagvik, Alaska Oil Spill Runway Canopy Reflectance Spectra (SVC)	1	7	https://ecosis.org/package/2017-utqia-vik--alaska-oil-spill-runway-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [93]	2017 Utqiagvik, Alaska Oil Spill Runway Plant Species Leaf Reflectance Spectra (SVC)	1	118	https://ecosis.org/package/2017-utqia-vik--alaska-oil-spill-runway-plant-species-leaf-reflectance-spectra--svc-
Vargas-Zesati et al. [94]	2017 Utqiagvik, Alaska Petasites frigidus Canopy Reflectance Spectra (SVC)	1	17	https://ecosis.org/package/2017-utqia-vik--alaska-petasites-frigidus-canopy-reflectance-spectra--svc-

Vargas-Zesati et al. [95]	2017 Utqiagvik, Alaska Plant Species Leaf Reflectance Spectra (SVC)	1	85	https://ecosis.org/package/2017-utqia-vik--alaska-plant-species-leaf-reflectance-spectra--svc-
Vargas-Zesati et al. [96]	2018 Atqasuk, Alaska CALM Plots Canopy Reflectance Spectra (SVC)	1	64	https://ecosis.org/package/2018-atqasuk--alaska-calm-plots-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [97]	2018 Atqasuk, Alaska CALM Plots Canopy Reflectance Spectra (Uni)	1	90	https://ecosis.org/package/2018-atqasuk--alaska-calm-plots-canopy-reflectance-spectra--uni-
Vargas-Zesati et al. [98]	2018 Atqasuk, Alaska MISP Transect Canopy Reflectance Spectra (SVC)	1	50	https://ecosis.org/package/2018-atqasuk--alaska-misp-transect-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [99]	2018 Atqasuk, Alaska MISP Transect Canopy Reflectance Spectra (Uni)	1	250	https://ecosis.org/package/2018-atqasuk--alaska-misp-transect-canopy-reflectance-spectra--uni-
Vargas-Zesati et al. [100]	2018 Atqasuk, Alaska Plant Reflectance Spectra (SVC)	1	20	https://ecosis.org/package/2018-atqasuk--alaska-plant-reflectance-spectra--svc-
Vargas-Zesati et al. [101]	2018 Imnavait, Alaska CALM Plots Canopy Reflectance Spectra (SVC)	1	64	https://ecosis.org/package/2018-imnavait--alaska-calm-plots-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [102]	2018 Toolik, Alaska CALM Plots Canopy Reflectance Spectra (SVC)	1	64	https://ecosis.org/package/2018-toolik--alaska-calm-plots-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [103]	2018 Utqiagvik, Alaska CALM Plots Canopy Reflectance Spectra (SVC)	1	115	https://ecosis.org/package/2018-utqia-vik--alaska-calm-plots-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [104]	2018 Utqiagvik, Alaska CALM Plots Canopy Reflectance Spectra (Uni)	1	150	https://ecosis.org/package/2018-utqia-vik--alaska-calm-plots-canopy-reflectance-spectra--uni-
Vargas-Zesati et al. [105]	2018 Utqiagvik, Alaska Chukchi Coast Survey Canopy Reflectance Spectra (SVC)	1	38	https://ecosis.org/package/2018-utqia-vik--alaska-chukchi-coast-survey-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [106]	2018 Utqiagvik, Alaska Drain Ponds Reflectance Spectra (SVC)	1	61	https://ecosis.org/package/2018-utqia-vik--alaska-drain-ponds-reflectance-spectra--svc-
Vargas-Zesati et al. [107]	2018 Utqiagvik, Alaska ITEX Species Reflectance Spectra (SVC)	1	360	https://ecosis.org/package/2018-utqia-vik--alaska-itex-species-reflectance-spectra--svc-
Vargas-Zesati et al. [108]	2018 Utqiagvik, Alaska MISP Transect Canopy Reflectance Spectra (SVC)	1	250	https://ecosis.org/package/2018-utqia-vik--alaska-misp-transect-canopy-reflectance-spectra--svc-
Vargas-Zesati et al. [109]	2018 Utqiagvik, Alaska MISP Transect Canopy Reflectance Spectra (Uni)	1	300	https://ecosis.org/package/2018-utqia-vik--alaska-misp-transect-canopy-reflectance-spectra--uni-
Vargas-Zesati et al. [110]	2018 Utqiagvik, Alaska Pond Margins Canopy Reflectance Spectra (SVC)	1	44	https://ecosis.org/package/2018-utqia-vik--alaska-pond-margins-canopy-reflectance-spectra--svc-
Walker [111]	Alaska Arctic Vegetation ATLAS-1 (Atqasuk, Barrow, Iivotuk, Oumalik) Vegetation Plots	1	254	https://arcticatlas.geobotany.org/catalog/dataset/ava-ak-atlas-1-atqasuk-barrow-ivotuk-oumalik-vegetation-studies-edwards-et-al-2000
* Walshaw et al. [112]	Spectral Library of Antarctic Terrestrial Vegetation Species	5	501	https://datashare.ed.ac.uk/handle/10283/8763
Wolff [113], supplementary data to Wolff et al. [20]	Spectral Libraries Aapa Mire Vegetation	2	18	https://zenodo.org/records/15715647
Yang et al. [114]	Terrestrial Hyperspectral Reflectance Data and a Spectral Library for Arctic Plant Species	1	10	https://kpdc.kopri.re.kr/search/a8783cb5-a62b-4163-8b64-e2cd04456463

648 **5.2 Checklist: Best Practices for Field Spectroscopy Data** 649 **Collection and Sharing**

650 All data is valuable. This checklist seeks to help in campaign planning and data
651 management on the one hand. On the other hand, it suggests the means to categorise
652 the content level of provided ancillary data for future users. To make sure all data
653 gets the deserved attention and is in line with potential users needs for different
654 applications, we assigned tiers from level 1 to level 3. A living document is available
655 at [Spec-Lib-Wiki](#) and open to suggestions and comments from the community.

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Declarations

Data availability

The authors do not own the rights on the individual datasets. The reader is referred to the list of datasets including the sources in the Supplementary information.

Competing interests

The authors declare no competing interests.

Code availability

Code can be made available upon request to antonia.ludwig@uni-leipzig.de.

Author contribution

A.L.: Conceptualization, Methodology, Data Curation, Formal analysis, Visualization, Writing - Original Draft, Project administration S.S.: Investigation, Writing - Original Draft K.W.: Software, Data Curation, Visualization B.H.: Conceptualization, Writing - Review & Editing G.R.: Conceptualization, Writing - Review & Editing H.F.: Conceptualization, Funding acquisition, Supervision

Ethics approval and consent to participate

Not applicable.

Materials availability

Not applicable.

Consent for publication

Not applicable.

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Appendix A Additional figures



Fig. A1 The current version of the hyperspectral reflectance dataset features data from Antarctica from 7 research sites containing 518 single in-situ measurements. Projection: polar stereographic.

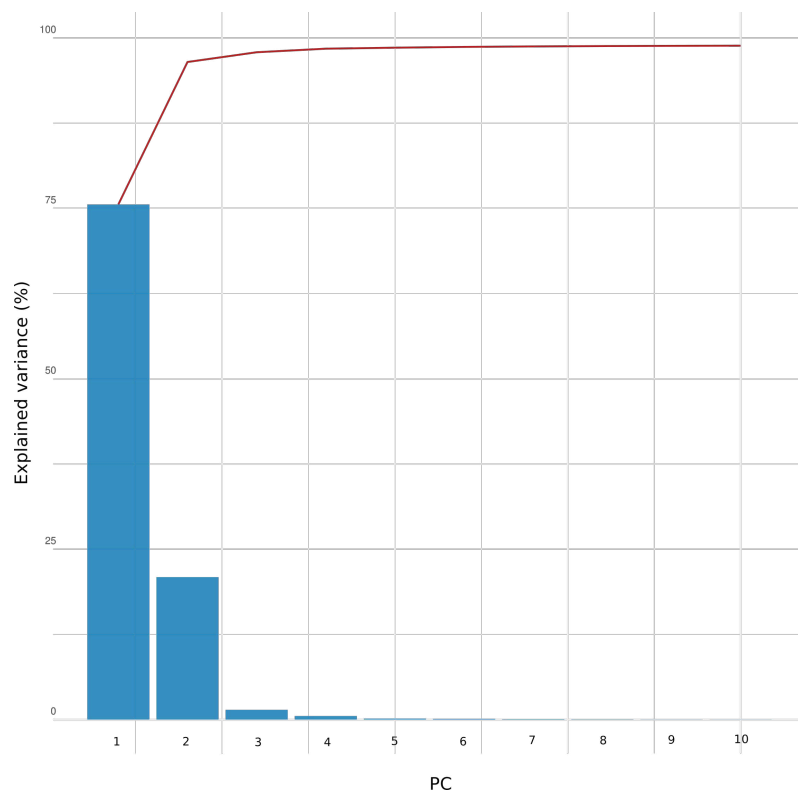


Fig. A2 Screeplot of the PCA presenting the explained variance per PC-axes (blue bars) and cumulative explained variance of the axes (red line). A PCA was performed based on 23,834 reflectance spectra from the cleaned dataset.

Table A1: Taxonomic composition of the Arctic tundra spectral library. Listed are all genera with species-level identification (n = 5,500 spectra, 18% of total database), grouped by functional group and family.

Group	Family	Genus	N species
Bryophytes	Amblystegiaceae	Drepanocladus	2
Bryophytes	Amblystegiaceae	Sanionia	1
Bryophytes	Andreaeaceae	Andreaea	1
Bryophytes	Aulacomniaceae	Aulacomnium	3
Bryophytes	Brachytheciaceae	Tomentypnum	1
Bryophytes	Bryaceae	Bryum	1
Bryophytes	Dicranaceae	Chorisodontium	1
Bryophytes	Dicranaceae	Dicranum	3
Bryophytes	Ditrichaceae	Ceratodon	1
Bryophytes	Grimmiaceae	Racomitrium	2
Bryophytes	Grimmiaceae	Schistidium	1
Bryophytes	Hylocomiaceae	Hylocomium	1
Bryophytes	Hylocomiaceae	Pleurozium	1
Bryophytes	Mniaceae	Plagiomnium	1
Bryophytes	Polytrichaceae	Pogonatum	1
Bryophytes	Polytrichaceae	Polytrichastrum	1
Bryophytes	Polytrichaceae	Polytrichum	3
Bryophytes	Rhytidiaceae	Rhytidium	1
Bryophytes	Sphagnaceae	Sphagnum	16
Lichens	Acarosporaceae	Pleopsidium	1
Lichens	Alectoriaceae	Alectoria	2
Lichens	Candelariaceae	Candelaria	1
Lichens	Candelariaceae	Candelariella	1
Lichens	Cladoniaceae	Cladina	3
Lichens	Cladoniaceae	Cladonia	16
Lichens	Lecanoraceae	Lecanora	1
Lichens	Lecanoraceae	Lecidella	1
Lichens	Nephromataceae	Nephroma	1
Lichens	Nostocaceae	Nostoc	1
Lichens	Pannariaceae	Psoroma	1
Lichens	Parmeliaceae	Asahinea	1
Lichens	Parmeliaceae	Bryoria	1
Lichens	Parmeliaceae	Cetraria	5
Lichens	Parmeliaceae	Dactylina	1
Lichens	Parmeliaceae	Evernia	1
Lichens	Parmeliaceae	Flavocetraria	2
Lichens	Parmeliaceae	Himantormia	1
Lichens	Parmeliaceae	Hypogymnia	1
Lichens	Parmeliaceae	Masonhalea	1

Lichens	Parmeliaceae	Melanelia	1
Lichens	Parmeliaceae	Parmelia	3
Lichens	Parmeliaceae	Parmeliopsis	1
Lichens	Parmeliaceae	Pseudephebe	1
Lichens	Parmeliaceae	Usnea	4
Lichens	Parmeliaceae	Vulpicida	1
Lichens	Parmeliaceae	Xanthoparmelia	1
Lichens	Peltigeraceae	Peltigera	4
Lichens	Pertusariaceae	Ochrolechia	1
Lichens	Physciaceae	Physconia	1
Lichens	Porpidiaceae	Porpidia	1
Lichens	Prasiolaceae	Prasiola	1
Lichens	Rhizocarpaceae	Rhizocarpon	2
Lichens	Sphaerophoraceae	Sphaerophorus	1
Lichens	Stereocaulaceae	Pilophorus	1
Lichens	Stereocaulaceae	Stereocaulon	2
Lichens	Teloschistaceae	Caloplaca	2
Lichens	Teloschistaceae	Xanthoria	1
Lichens	Trapeliaceae	Placopsis	1
Lichens	Trapeliaceae	Trapeliopsis	1
Lichens	Umbilicariaceae	Umbilicaria	3
Vascular plants	Apiaceae	Aegopodium	1
Vascular plants	Apiaceae	Heracleum	1
Vascular plants	Asteraceae	Hieracium	1
Vascular plants	Asteraceae	Petasites	1
Vascular plants	Betulaceae	Alnus	4
Vascular plants	Betulaceae	Betula	5
Vascular plants	Caryophyllaceae	Colobanthus	1
Vascular plants	Caryophyllaceae	Stellaria	1
Vascular plants	Crassulaceae	Sedum	1
Vascular plants	Cupressaceae	Juniperus	1
Vascular plants	Cyperaceae	Carex	4
Vascular plants	Cyperaceae	Eriophorum	6
Vascular plants	Empetraceae	Empetrum	1
Vascular plants	Equisetaceae	Equisetum	3
Vascular plants	Ericaceae	Arctostaphylos	4
Vascular plants	Ericaceae	Cassiope	1
Vascular plants	Ericaceae	Kalmia	1
Vascular plants	Ericaceae	Ledum	3
Vascular plants	Ericaceae	Loiseleuria	1
Vascular plants	Ericaceae	Rhododendron	2
Vascular plants	Ericaceae	Vaccinium	3
Vascular plants	Ericaceae	Vaccinium	1
Vascular plants	Fabaceae	Lupinus	1
Vascular plants	Geraniaceae	Geranium	1

Vascular plants	Iridaceae	Iris	1
Vascular plants	Juncaceae	Juncus	1
Vascular plants	Juncaceae	Luzula	3
Vascular plants	Liliaceae	Tofieldia	1
Vascular plants	Liliaceae	Tulipa	1
Vascular plants	Onagraceae	Chamerion	1
Vascular plants	Papaveraceae	Papaver	2
Vascular plants	Pinaceae	Larix	1
Vascular plants	Pinaceae	Picea	3
Vascular plants	Poaceae	Alopecurus	2
Vascular plants	Poaceae	Arctagrostis	1
Vascular plants	Poaceae	Arctophila	1
Vascular plants	Poaceae	Calamagrostis	1
Vascular plants	Poaceae	Deschampsia	1
Vascular plants	Poaceae	Dichanthelium	1
Vascular plants	Poaceae	Dupontia	1
Vascular plants	Poaceae	Festuca	1
Vascular plants	Poaceae	Poa	2
Vascular plants	Polygonaceae	Bistorta	1
Vascular plants	Polygonaceae	Polygonum	2
Vascular plants	Primulaceae	Dodecatheon	1
Vascular plants	Pteridaceae	Pellaea	1
Vascular plants	Ranunculaceae	Ranunculus	1
Vascular plants	Rosaceae	Dasiphora	1
Vascular plants	Rosaceae	Dryas	3
Vascular plants	Rosaceae	Potentilla	1
Vascular plants	Rosaceae	Rosa	1
Vascular plants	Rosaceae	Rubus	3
Vascular plants	Rosaceae	Sorbus	1
Vascular plants	Salicaceae	Populus	2
Vascular plants	Salicaceae	Salix	14
Vascular plants	Saxifragaceae	Saxifraga	5
Vascular plants	Scrophulariaceae	Pedicularis	2

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