



Trait-based mapping of functionally diverse tundra types using hyperspectral EnMap data

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Abstract.

The Arctic is undergoing rapid environmental change, with vegetation responses that feed back into surface energy balance, permafrost dynamics, and biogeochemical cycling at global scale. Yet existing satellite-based monitoring products, including broadband vegetation indices and categorical land cover maps, lack the sensitivity to detect early, process-driven shifts in vegetation function that precede visible compositional change. Plant functional traits retrieved from space-borne hyperspectral imagery offer a more physiologically based alternative, enabling spatially continuous characterisation of ecosystem function independently of species identity or land cover class. Here, we use EnMAP hyperspectral imagery and a convolutional neural network to retrieve 20 plant functional traits across Arctic tundra spotlight acquisitions spanning the North American Arctic and Greenland from 2022 to 2024. We characterise the structure of the resulting trait space, introduce pixel originality as a spatially continuous measure of functional uniqueness derived from multivariate trait distributions, and assess the capacity of trait-based predictors to differentiate vegetation types from the Circumpolar Arctic Land Use map using Random Forest models. Two principal components captured $\approx 86\%$ of total trait variability, organised along axes corresponding to the leaf economics spectrum and pigment composition. Pixel originality was almost entirely predictable from the selected traits ($R^2 \approx 0.97$), with LAI, LMA, and carbon content as the dominant drivers, and showed smooth spatial gradients consistent with microtopographically structured tundra landscapes rather than discrete functional hotspots. Trait-based Random Forest classification of vegetation types achieved a mean accuracy of $\approx 73\%$, demonstrating that functional traits alone carry substantial discriminatory power for broad vegetation class differentiation. These findings establish EnMAP-derived functional traits as a robust basis for landscape-scale monitoring of Arctic tundra diversity and function, with pixel originality offering a promising tool for tracking functional change across rapidly transforming ecosystems.

1 Introduction

The Arctic is warming at nearly four times the global average rate, driving rapid and widespread changes in vegetation structure, permafrost integrity, and biogeochemical cycling (Myers-Smith et al., 2020; Bjorkman et al., 2018; Frost et al., 2025). Vegetation responses are diverse and often concurrent: shrub expansion into previously herb- and moss-dominated communities



alters canopy height and snow interception, wetland formation and drainage reshape carbon and water fluxes, and widespread moss and lichen decline reduces the insulating capacity of the ground layer, accelerating permafrost thaw (Liljedahl et al., 2016; Mallen-Cooper et al., 2023; Schuur et al., 2024; Bjorkman et al., 2020). These changes feed back into surface energy balance and nutrient cycling with consequences that extend well beyond the region (Post et al., 2019). Yet vegetation cover and species composition alone provide an incomplete picture of these dynamics. Ecosystem responses to environmental change are fundamentally mediated by plant function. The physiological and biochemical strategies by which plants acquire resources, tolerate stress, and cycle nutrients can shift substantially before any visible change in community composition or land cover is detectable (Violle et al., 2007). Monitoring vegetation function, rather than structure or cover alone, is therefore essential for detecting early signals of ecosystem change and for understanding the processes that drive them. Achieving this at the spatial and temporal scales relevant for regional assessment remains one of the central challenges in Arctic ecology (Walker et al., 2025).

Satellite remote sensing is an essential tool for Arctic vegetation monitoring, given the logistical constraints and short growing seasons that severely limit the spatial and temporal coverage of field-based observations across remote Arctic landscapes (Beamish et al., 2020; Nelson et al., 2022; Everest et al., 2026; Walker et al., 2025). By providing repeated, spatially continuous observations across wide areas, satellite sensors capture vegetation dynamics at scales that ground surveys cannot match. In practice, monitoring efforts have relied on a limited set of products designed for global applications. Multispectral sensors such as Landsat, MODIS, and Sentinel-2 form the backbone of these efforts, delivering time series of broadband reflectance from which vegetation indices and biophysical variables are routinely derived. The physical basis for this lies in the interaction between solar radiation and plant tissue: pigments such as chlorophyll absorb strongly in the visible domain, leaf cell structure drives high reflectance in the near-infrared, and liquid water attenuates radiation in the shortwave infrared. These spectrally distinct responses allow satellite observations to be linked to vegetation properties in a physically meaningful way, forming the foundation of optical vegetation remote sensing (Gamon et al., 2019; Cavender-Bares et al., 2025). Broadband indices such as NDVI (Normalized Difference Vegetation Index, Tucker (1979)) and LAI (Leaf Area Index,) exploit these contrasts between spectral regions to track large-scale phenological patterns and interannual greenness trends, and have been widely used to document greening and browning dynamics across the Arctic (Myers-Smith et al., 2020; Frost et al., 2025). Categorical vegetation and land cover maps, such as the CAVM (Circum-Arctic Vegetation Map, Reynolds et al. (2019)) and CALU (Circum-Arctic Landcover Units, Bartsch et al. (2024)), complement these time series by describing the spatial distribution of plant communities across the circum-Arctic region. Yet both approaches carry important limitations in the Arctic context. Broadband indices are insensitive to physiological status, nutrient allocation, or stress responses that occur without structural change in the canopy (Cunliffe et al., 2020), while categorical maps assume within-class homogeneity and temporal stability, obscuring gradual, process-driven shifts in ecosystem function (Yang et al., 2026; Nelson et al., 2022). Together, these products risk missing early or subtle changes in vegetation state that precede detectable compositional turnover.

The convergence of imaging spectroscopy and machine learning offers a fundamentally different perspective, one that moves beyond categorical summaries toward continuous, physiologically grounded characterisations of vegetation (Kattenborn et al. (2021); Cherif et al. (2023); Mederer et al. (2025a)). This interface is particularly powerful for biodiversity assessments, as it



enables the translation of spectral complexity into ecologically meaningful signals at spatial scales previously inaccessible to field science. Space-borne imaging spectroscopy enables the retrieval of such traits at landscape to regional scales. By resolving continuous spectral signatures across the visible and shortwave infrared, hyperspectral sensors capture subtle absorption features linked to leaf biochemistry and canopy structure that broadband instruments cannot resolve (Gamon et al., 2019; Cavender-Bares et al., 2025; Salko et al., 2024). Upcoming hyperspectral missions are making this capability operational at ecologically relevant scales. Recent advances in convolutional neural networks (CNNs) have further improved trait retrieval accuracy by exploiting the full spectral shape of hyperspectral data, learning non-linear relationships between reflectance patterns and plant properties that linear or index-based methods cannot capture (Kattenborn et al., 2021). Quantitative measures of leaf physiology, structure, and biochemistry, such as leaf mass per area, nitrogen content, and pigment concentrations, describe how plants balance resource acquisition and conservation, directly linking vegetation state to productivity, stress, and nutrient cycling (Violle et al., 2007). Critically, traits can characterise ecosystem function independently of species identity (but also van Der Plas et al. (2020)), making them well suited to the fine-scale functional mosaics typical of Arctic tundra, where diverse plant strategies coexist within individual remote sensing pixels and where functional shifts may precede compositional change (Heijmans et al., 2022; Yang et al., 2026).

While imaging spectroscopy and CNN-based trait retrieval have advanced considerably, most large-scale applications focus on temperate or tropical ecosystems, and existing retrieval models are rarely trained on Arctic vegetation with its distinctive spectral characteristics (Salko et al., 2024). The Arctic thus represents both an urgent and underexplored target for hyperspectral monitoring. Its strong functional heterogeneity, driven by microtopographic and soil moisture gradients, means that ecologically meaningful variation is packed into fine spatial scales (Heijmans et al., 2022), yet the low canopy height, variable illumination, and the distinctive spectral signatures of lichens and bryophytes complicate the ecological interpretation of the spectral signal (Beamish et al., 2020; Nelson et al., 2022). At the same time, the rapid environmental changes already documented across the region (Heijmans et al., 2022; Frost et al., 2025; Hu et al., 2015) make it precisely the kind of system where sensitive, continuous monitoring is most needed (Walker et al., 2025).

Plant functional traits retrieved from hyperspectral imagery offer a more process-sensitive basis for such monitoring. Rather than assigning pixels to discrete classes, trait retrieval yields continuous, physiologically grounded estimates of vegetation state that can reveal functional gradients and detect subtle shifts in ecosystem function before they manifest as compositional change. To move from individual trait predictions toward an integrated measure of functional diversity, we introduce pixel originality, a metric that quantifies how functionally distinct a given location is relative to the broader multivariate trait space captured by the image. Derived from principles of functional diversity and adapted to imaging spectroscopy, pixel originality provides a spatially continuous, classification-free index of tundra trait diversity, capable of identifying functional hotspots that may remain undetected in spatially restricted field campaigns or coarse categorical maps. Together, these approaches open new possibilities for supporting Arctic vegetation monitoring at ecologically relevant scales.

Building on this rationale, we leverage EnMAP hyperspectral imagery and CNN-based trait retrieval to deliver spatially continuous assessments of vegetation function across Arctic tundra. Specifically, we aim to: (1) identify a representative subset of EnMAP-derived traits for describing tundra vegetation function; (2) characterise the structure of the Arctic trait space and



its ecological gradients; and (3) quantify how well trait-derived metrics, including pixel originality, explain spatial patterns of
95 functional diversity and differentiate CALU vegetation classes.

2 Material and Methods

2.1 Study Area

The study focuses on the Arctic biome, a high-latitude region characterized by extreme climatic conditions, permafrost-
dominated soils, and a short growing season. Mean annual temperatures generally remain below 0 °C, and the landscape
100 is shaped by frost-related processes such as cryoturbation and polygonal ground formation. Vegetation is predominantly com-
posed of low-stature plant communities, including mosses, lichens, graminoids, and dwarf shrubs. They typically form complex
mosaics across gradients of soil moisture, temperature, and topography (Raynolds et al., 2019, 2006). Most of the EnMAP
scenes analysed in this study are located within the North American Arctic, encompassing regions of Alaska and northern
Canada. This portion of the Arctic biome spans a broad range of climatic and ecological gradients, from maritime tundra in
105 western Alaska to cold, dry polar deserts of the Canadian High Arctic. The dominant vegetation types include graminoid and
moss tundra in lowland areas, dwarf-shrub tundra on well-drained uplands, and extensive wetlands and peatlands in coastal
and permafrost-depressed zones (Raynolds et al., 2019). Permafrost and active-layer dynamics strongly influence hydrology
and vegetation distribution, while microtopographic variation creates fine-scale habitat heterogeneity. Over recent decades,
the North American Arctic has undergone pronounced environmental change, including increasing shrub cover, altered soil
110 moisture regimes, and longer growing seasons (Myers-Smith et al., 2020; Frost et al., 2025).

2.2 Data

2.2.1 EnMap data

We used hyperspectral imagery from the German EnMAP mission, which measures reflected solar radiation across the visible
to short-wave infrared range ($\approx 420 - 2450nm$) in more than 240 contiguous bands, at a spatial resolution of 30 m $\times$ 30 m. The
115 Level 2A imagery was pre-processed by Mederer et al. (2025b). Due to acquisition limitations, the available EnMAP images
do not provide complete spatial coverage of the Arctic tundra. Our analysis was therefore restricted to the scenes available for
our study area in the time period from 2022 to 2024 (Fig. 1). All images were atmospherically corrected to surface reflectance
prior to analysis by Mederer et al. (2025a). In order to mask out water bodies, the NDVI was calculated for the individual
scenes using band 72 as centre near infrared (NIR) and band 46 as centre red wavelength region. All pixels with NDVI < 0.1
120 were removed from the images to exclude non-vegetated areas or water bodies. The NDVI threshold was set comparably low
due to include sparse vegetation with low pigment concentrations as well as lichen and moss surfaces (see also Erlandsson
et al. (2023) and Jia et al. (2004)).

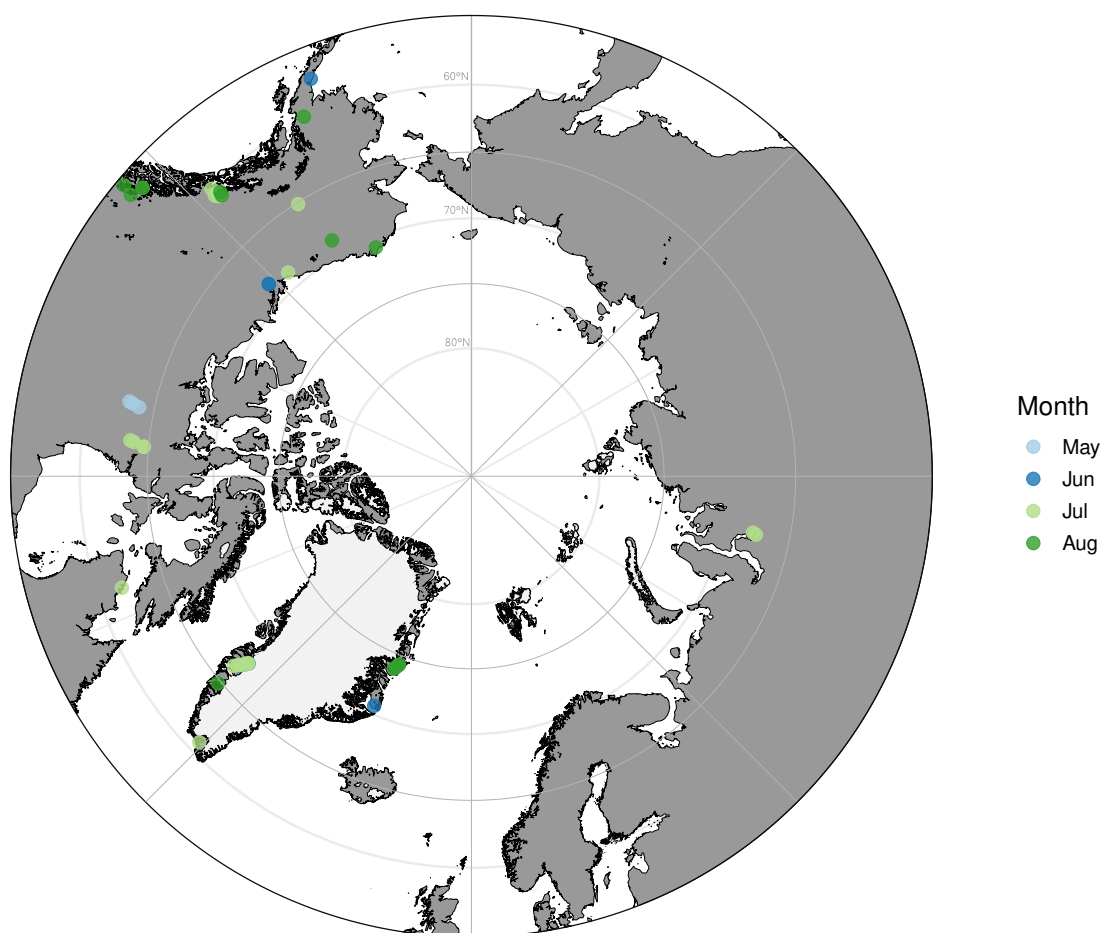


Figure 1. Map of the Arctic from a North-pole centred perspective showing the centre coordinates of all used EnMAP tiles in this study. The spatial coverage of the available EnMAP tiles for the time period of 2022 to 2024 in the Arctic biome was mainly restricted to North America and Greenland. From the available hyperspectral data, we retrieved a set of 20 plant traits using a convolutional neural network, which was first developed by Cherif et al. (2023) and adapted to EnMAP data by Mederer et al. (2025a). This map was produced using the *ggOceanMaps*-package (V.2.20, Vihtakari (2024)).



2.2.2 Land cover types

In order to relate the derived traits to pixel-based land cover types, we used the 'Circum Arctic Land Cover Units' dataset (hereafter 'CALU') by Bartsch et al. (2024). It provides a land cover classification of Arctic regions North of the treeline at a high spatial resolution of 10 m. The CALU is derived from a fusion of optical multispectral data (Sentinel-2) and C-band synthetic aperture radar data (Sentinel-1), enabling the differentiation of vegetation structure, wetness gradients and other surface characteristics. The classification distinguishes multiple land cover types across moisture and shrub-growth gradient, thereby providing thematic detail that is particularly suited for mapping functional trait variation and ecosystem heterogeneity in tundra landscapes. CALU differentiates tundra types along gradients of moisture, shrub height, and vegetation structure, making it suitable for linking functional traits to land cover classes. Spatial gaps exist in the dataset due to cloud cover, radar limitations, or processing constraints. The dataset provides a set of nine simplified vegetation units that incorporate different fine-scale descriptions of vegetation types in accordance with the Circum-Arctic Vegetation Map (Raynolds et al., 2019). For example, the unit *dwarf-to-low-shrub tundra* includes several more detailed vegetation descriptions, such as "dry to moist tundra, prostrate low shrubs" or "moist tundra, dense dwarf and low shrubs" (see Bartsch et al. (2024)). CALU was used to assign each EnMAP-pixel to a land cover class, enabling stratified trait mapping and assessment of functional diversity across tundra types. Pixels classified as water, ice or permanent snow were removed in order to obtain pixels covering vegetation only.

2.3 Analysis

Using a CNN developed by Cherif et al. (2023) and adapted to EnMAP imagery by Mederer et al. (2025a), a set of 20 plant functional traits was predicted for all EnMAP scenes available for the Arctic (from 60° N) from 2022 to 2024 (upper part of Fig. 2). The CNN was trained on a data collection in which hyperspectral and plant trait measurements from various sources have been integrated into a single training dataset for vegetation trait predictions (Cherif et al., 2025). For further details on model architecture and python code, the reader is referred to Cherif et al. (2023, 2026) and Mederer et al. (2025a).

Based on random sample of 10,000 random pixels from across all EnMAP tiles, the 20 traits per scene were tested for multicollinearity using Pearson's correlation test, which was highly significant for multiple traits (see Appendix Fig. A1, $r > 0.9$ in most of the cases.). Based on this, eight representative traits which contribute to three aspects of biodiversity were selected for further analysis:

1. structural diversity: Leaf Area Index (LAI in m^2/m^2), leaf mass per area (LMA in mg/cm^2)
2. functional diversity: leaf carbon content (C in mg/cm^2), nitrogen content (N in mg/cm^2), Equivalent Water Thickness (EWT in mg/cm^2)
3. phenological diversity: chlorophyll content (Chl in $\mu g/cm^2$), carotenoid content (Car in $\mu g/cm^2$), anthocyanin content (Antho in $\mu g/cm^2$)

To reduce the dimensionality of the data and extract the dominant patterns of trait variation, we applied a Principal Component Analysis (PCA) using the *FactoMineR*-package in R (Lê et al., 2008). The resulting components of a PCA provide a

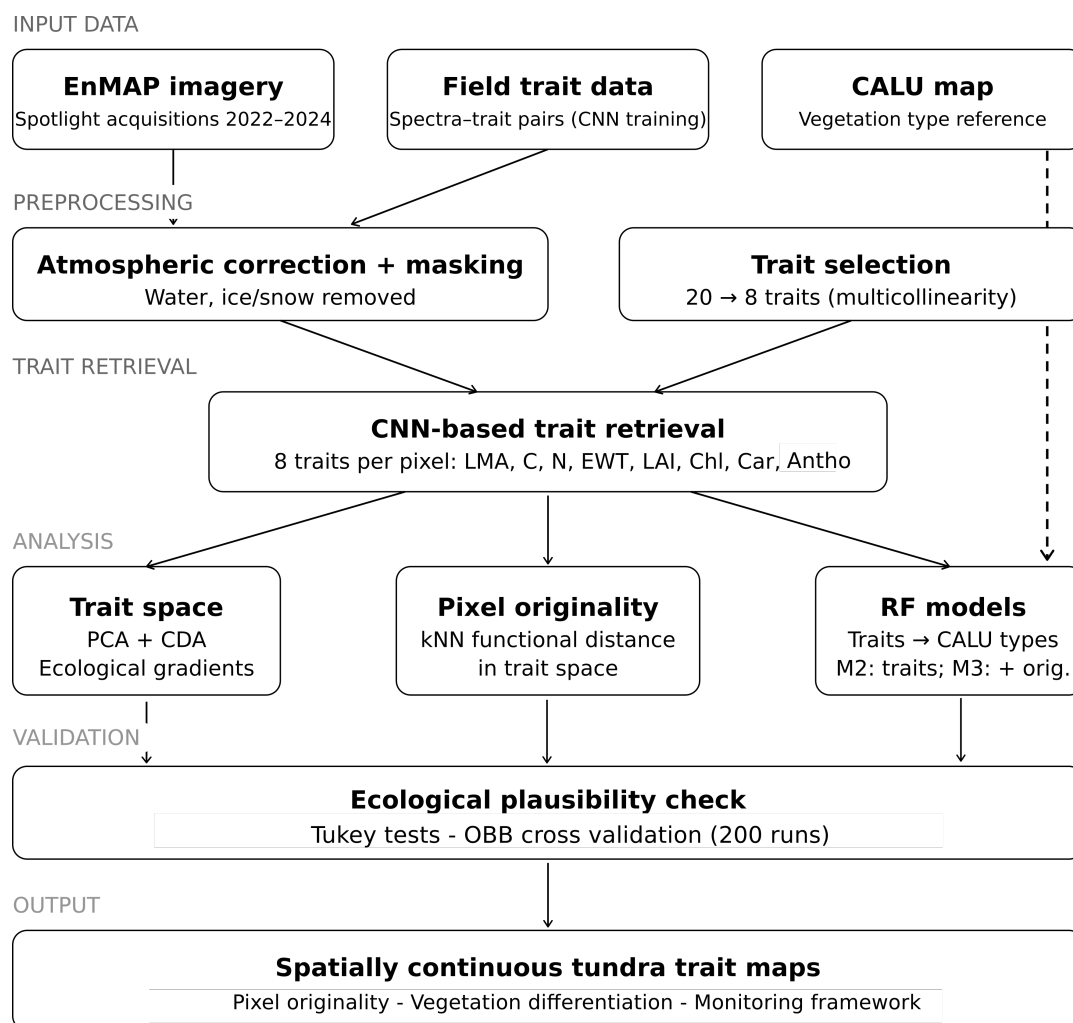


Figure 2. Analytical workflow. EnMAP hyperspectral imagery and field-based trait–spectra pairs served as primary inputs. Following atmospheric correction and pixel masking, a convolutional neural network (CNN) was used to retrieve 20 plant functional traits per pixel. The resulting trait data informed three parallel analyses: (1) dimensionality reduction and canonical discriminant analysis of the trait space, (2) derivation of pixel originality as a measure of functional uniqueness, and (3) Random Forest classification of Circum-Arctic Land Use (CALU) vegetation types. All classification models were evaluated using out-of-bag (OOB) cross-validation across 200 repeated runs. Trait abbreviations: LMA - leaf mass per area, C - carbon content, N - nitrogen content, EWT - Equivalent Water Thickness, LAI - Leaf Area Index, Chl - leaf chlorophyll content, Car - leaf carotenoid content, Atc - anthocyanin content.



155 compressed n-dimensional representation of the multivariate trait space (Díaz et al., 2016; Mouillot et al., 2021; Parsons et al., 2009). In order to reduce the computational effort, we first sampled 10,000 pixels with the respective trait values from each EnMAP scene. All trait values were centred and standardized ($mean = 0$, $sd = 1$) before conducting the PCA. The axes that contained the major part of the variability in the data ($\approx 80\%$) were chosen as representatives of the trait space throughout the rest of the study. In a second step, the full EnMAP image data were projected into the previously computed PCA space. To
 160 ensure comparability across the spatially scattered EnMAP scenes, each pixel spectrum was standardized using the mean and standard deviation values derived from the original PCA input data. As a result, the EnMAP scenes are representatives of the trait space and not the individual traits per se.

To quantify the functional uniqueness of each pixel, we calculated pixel originality, a measure of how spectrally distinct a pixel is relative to its neighbours in the multivariate hyperspectral space. Specifically, we used a k-nearest neighbours
 165 (kNN) approach, in which each pixel's distance to its k closest neighbours in a k-neighbourhood was computed in the PCA-reduced trait space derived from EnMAP spectra. Pixels with larger average distance to their neighbours were considered more "original", indicating unique combinations of spectral characteristics representing in the functional trait space.

In order to assess if CALU classes differ in the multivariate trait space, we applied a multivariate analysis of variance (MANOVA) with Pillai's trace as multivariate test statistic using the *vegan*-package (Oksanen et al., 2025). Pillai's trace is
 170 considered one of the most robust multivariate tests, as it is less sensitive to violations of assumptions. CALU class was treated as the independent variable, all traits (numeric) are the dependent variables. Additionally, we computed a Canonical Discriminant Analysis (CDA) applying the *candisc*-package (Friendly and Fox, 2024) and density visualizations to illustrate the separation of CALU types in the trait space. CDA finds the linear combinations of traits that maximize the separation between predefined groups (here, the CALU types). Each point in the CDA plot is a pixel, positioned based on its trait values projected
 175 onto these axes. Pixels that are closer together have similar trait combinations, pixels farther apart differ more strongly. CDA plots were created in *ggplot2* (Wickham, 2016), where a confidence level of 65% was selected for calculating ellipses around the centroid of a given vegetation group. The centroid is the mean trait position of that group in canonical trait space.

Finally, we applied three Random Forest (RF) models (Breiman, 2001) using the *ranger*-package (Wright and Ziegler, 2017). RF is an ensemble learning method based on bootstrap aggregation of decision trees, which provides robust predictions and
 180 internal estimates of prediction error through out-of-bag (OOB) samples. **Model 1** was implemented as an RF regression to identify the plant functional traits driving pixel originality. **Model 2 and 3** were applied as RF classifiers to predict Arctic tundra land cover types, with Model 2 using only EnMAP-derived trait information, and Model 3 combining traits and pixel originality. The *ranger* implementation trains each tree on a bootstrap sample of the full dataset and computes OOB predictions for observations excluded from that bootstrap, effectively providing an internal cross-validation. All models were run with 200
 185 repetitions, 500 trees per forest, and a subset of three predictors considered at each split ($mtry=3$). Model performance was evaluated based on the averaged mean accuracy (ACC) and Cohen's kappa (κ) from 200 iterations. κ indicates the extent to which agreement between the observed and expected outcomes is better than what would be expected by random chance (-1 = completely random, 1 = perfect prediction). Variable importance was assessed using the impurity-based (Gini) importance measure implemented in the ranger random forest algorithm (Nembrini et al., 2018; Wright and Ziegler, 2017). For each of



the 200 repetitions, a forest was fit with a unique random seed, and the importance of each predictor was quantified by the total decrease in node impurity attributable to that variable across all trees. Importance values were then aggregated across repetitions to provide stable estimates of each variable's contribution to model predictions (lower part of Fig. 2).

If not stated otherwise, all analyses were performed using R Statistical Software (R version 4.5.0, R Core Team (2025)).

3 Results

Results from the dimensionality reduction of the selected traits and pixels using PCA showed that the first two axes together represent $\approx 86\%$ of the variation in the data. Consequently, PC1 and PC2 were selected as representatives of the trait space for the rest of the study. The density distribution showed a continuous but structured trait space: PC1 is mainly dominated by traits associated with the leaf economics spectrum, that is LMA, C content, LAI, N content (N) and EWT (Fig. 3). In contrast, PC2 is dominated by pigment contents (chlorophyll, carotenoids, and anthocyanins).

In general, pixel originality had a narrow range with values from 0 to 0.3 (see Appendix Fig. A2) that are distributed in spatial clusters (see Fig. 4 as a representative example). The majority of pixels fall in the moderate region. Only in very few cases of exceptionally high pixel originality have been detected across the available EnMAP scenes.

The RF regression model revealed that EnMAP-derived traits were a strong predictor for pixel originality. Across 200 runs, the model consistently achieved high prediction accuracy around 97% (Fig. 5 B) and a root mean squared error (RSME) of ≈ 0.025 . Based on Gini index, the top contributing traits were LAI with a mean relative importance of $\approx 22\%$ across all runs, followed by LMA, C content and carotenoid content with mean relative importance around $\approx 12\%$ (Fig. 5 A).

The CDA shows that the separation of CALU classes based on EnMAP-derived traits results in a partial but meaningful separation of CALU classes along Can1 and Can2 (Fig. 6). The CALU classes form partly overlapping but still structured clouds. The first canonical axis (Can1) alone explains $\approx 58\%$ of the between group variation. Together with Can2, it captures $\approx 75\%$ of all between-group structure. Can3 adds $\approx 10\%$, the remaining variation is split among the Can4 to Can13, which contain very low discriminative power (Fig. 6 A).

Figure 7 provides further insights into the underlying trait patterns across the different CALU types. Wetlands exhibit in general broad ranges of values across the different traits. While showing broad standard deviations, the trait mean is close to the global mean. Wetland EWT and LAI are exceptions with mean values that exceed the global mean substantially. Cryptogams (i.e. lichen and moss) have trait means close to the global mean or slightly higher. Carbon content, LAI, LMA and nitrogen content are lower compared to the global mean. Based on EnMAP-derived traits, the graminoid group is characterized by low pigment contents. That includes chlorophylls, as well as carotenoids and anthocyanins. Also carbon and nitrogen content are below the global mean, while LAI values are generally higher and come with broader standard deviation compared to the other CALU types. Forests are not the aim of this study and not part of the tundra biome. However, the delineation of tundra requires a clear characterization of forest habitats. Therefore, we include forests in the detailed description of CALU types. Their trait means are higher compared to the global mean considering all regarded traits in this study. They stand out in terms of high carbon and nitrogen content as well as LMA. Dwarf-to-low-shrub tundra (hereafter 'shrub tundra') is characterized by trait

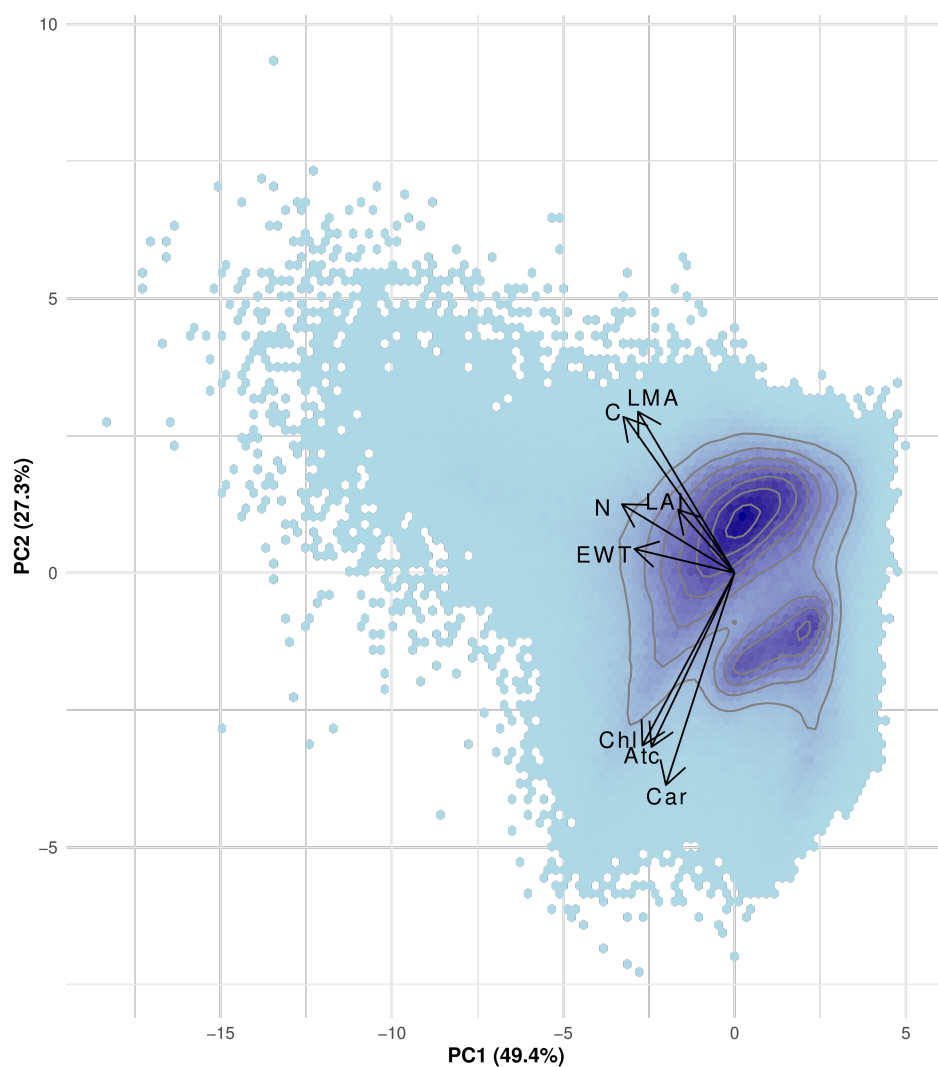


Figure 3. Trait space represented by PC1 and PC2 with contour lines (grey) and a smooth density colour gradient from dark blue (high point density) to light blue (low point density). Arrows show the trait loadings and direction on the PC axes. Abbreviations: LMA - leaf mass per area, LAI - leaf area index, C - carbon content, N - nitrogen content, EWT - equivalent water thickness, Chl - chlorophyll content, Car - carotenoid content, Atc - anthocyanin content.

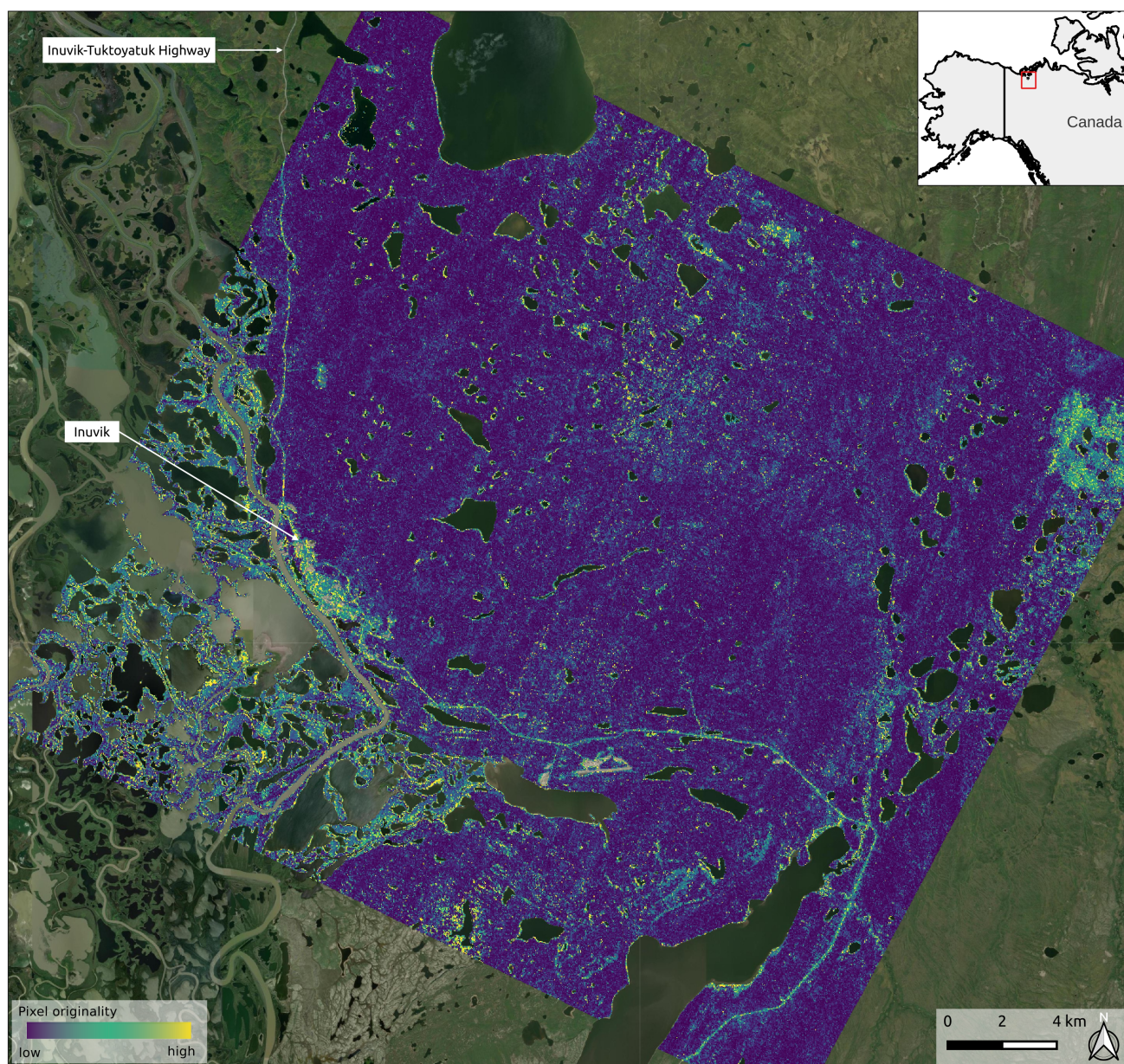


Figure 4. Pixel originality for an exemplary EnMAP scene covering the Inuvik region (acquisition date: 02.07.2024). Pixel originality was calculated in the spectral trait space that was derived from eight pre-selected EnMAP-derived plat traits. The colour gradient reflects the uniqueness of the pixels referring to a $k = 30$ pixel neighbourhood. This map was created using the Free and Open Source QGIS (QGIS Development Team, 2025). Background map: ESRI world imagery (ESRI, 2025). Scale: 1:735000. EPSG:32608 - WGS 84 / UTM zone 8N.

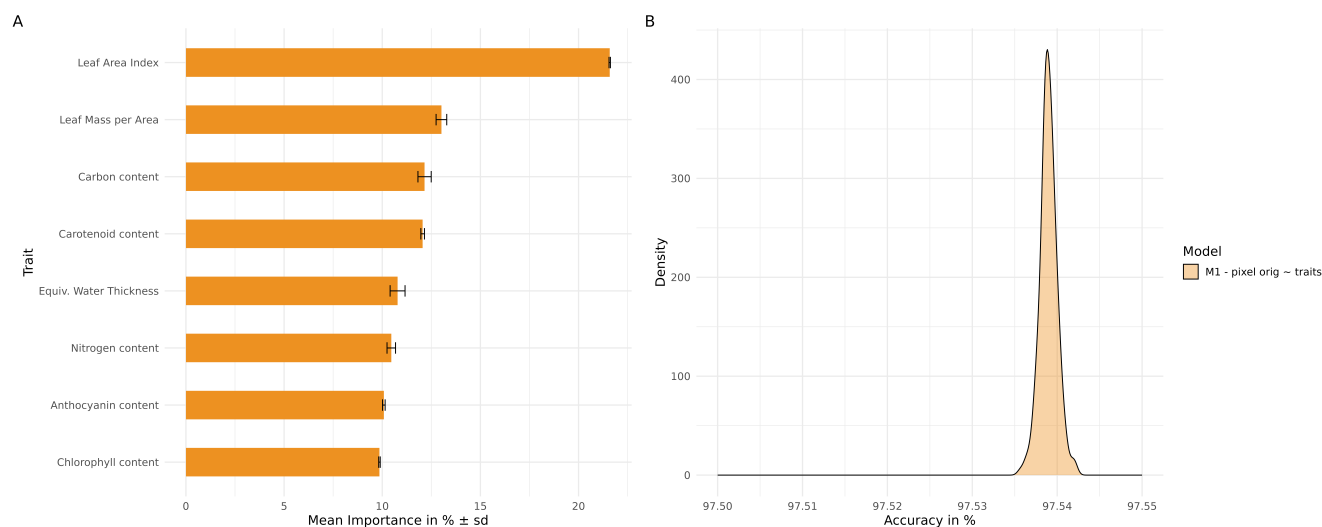


Figure 5. Random Forest regression results across 200 runs with EnMAP-derived traits as predictors for pixel originality. (A) Mean importance $\pm$ sd in % of the individual traits to the overall mean prediction accuracy of the RF regression. (B) Density distribution of model accuracy across 200 runs. Mean accuracy across runs: $\approx 97.54\%$ and mean root mean square error (RMSE) across runs: $0.025 \pm 1.0e-05$.

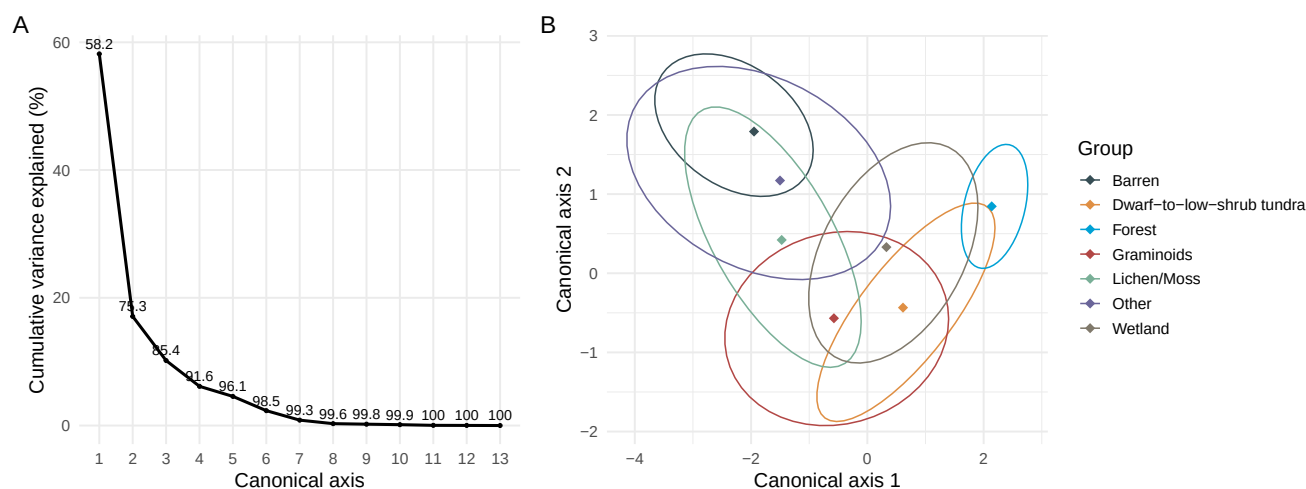


Figure 6. (A) Cumulative variance explained by the single axes of the CDA. (B) Separation of CALU classes in the CDA trait space. The ellipses enclose $\approx 65\%$ of the samples from a given vegetation class. The centroids (squares) show the mean trait position of the respective class in canonical trait space.



values around or the global mean. Based on the here employed CNN for trait prediction, barren lands exhibit exceptionally high pigment content and EWT, while all other traits are far below the global mean. Results from a consecutive Tukey test provide further detail about the group separation in the trait space. The three leaf pigments show a similar pattern. Graminoids and shrubs are not significantly different in terms of their pigment contents while all other CALU types are well separated in individual groups (see the letters in Fig. 7 for the results of the Tukey test). Except 'other', graminoids and cryptogams, all CALU types differ significantly in carbon content. The same pattern is apparent concerning LMA. Another pattern was revealed by the Tukey test regarding LAI: while wetlands, graminoids, forests and shrub tundra are associated to the same group, lichen/ moss, 'other' and barren lands significantly differ in their LAI ranges. Regarding LMA, cryptogams and graminoids are combined in the same group while the other CALU types show significantly different mean values for this trait.

The RF classification models 2 (traits only) and 3 (traits & pixel originality) both achieve similar mean accuracy of $\approx 73\%$ across 200 runs (Tab. 1 and Fig. 8, out-of-bag error rates can be found in the Appendix, Fig. A3). The mean importance of predictors follows a similar pattern. In both models, LAI is the most important predictor (mean importance $\approx 22\%$), followed by the other predictors with mean relative importance between 9% - 12% in both models. Pixel originality as additional predictor achieved a mean relative importance of $\approx 9\%$, ranking around the least contributing factors for CALU classification in model 3.

Table 1. Results from the Random Forest classification with two different predictor sets: (1) the spectral traits only (EnMAP-based, model 2), and (2) the traits in combination with pixel originality (model 3). Both the models were trained using an out-of-bag bootstrapping implemented in the *ranger*-package in R which includes cross-validation. Specific model parameters: runs= 200, ntree = 500, mtry = 3. ACC: model accuracy (average over 200 iterations), mean κ = Cohen's kappa (average over 200 iterations) Range κ : -1 = completely random, 1 = perfect prediction.

Model	mean ACC	sd ACC	mean κ	sd κ
M2: Traits only	0.73	< 0.05	0.52	< 0.05
M3: Traits & originality	0.74	< 0.05	0.53	< 0.05

4 Discussion

This study demonstrates that plant functional traits retrieved from EnMAP hyperspectral imagery provide a robust and ecologically meaningful basis for characterising tundra vegetation diversity and function at landscape scale. We discuss our findings along three thematic axes: the utility of pixel originality as a continuous measure of functional diversity, the structure of the EnMAP-derived trait space and its ecological interpretation, and the potential and limitations of trait-based approaches for classifying Arctic vegetation types.

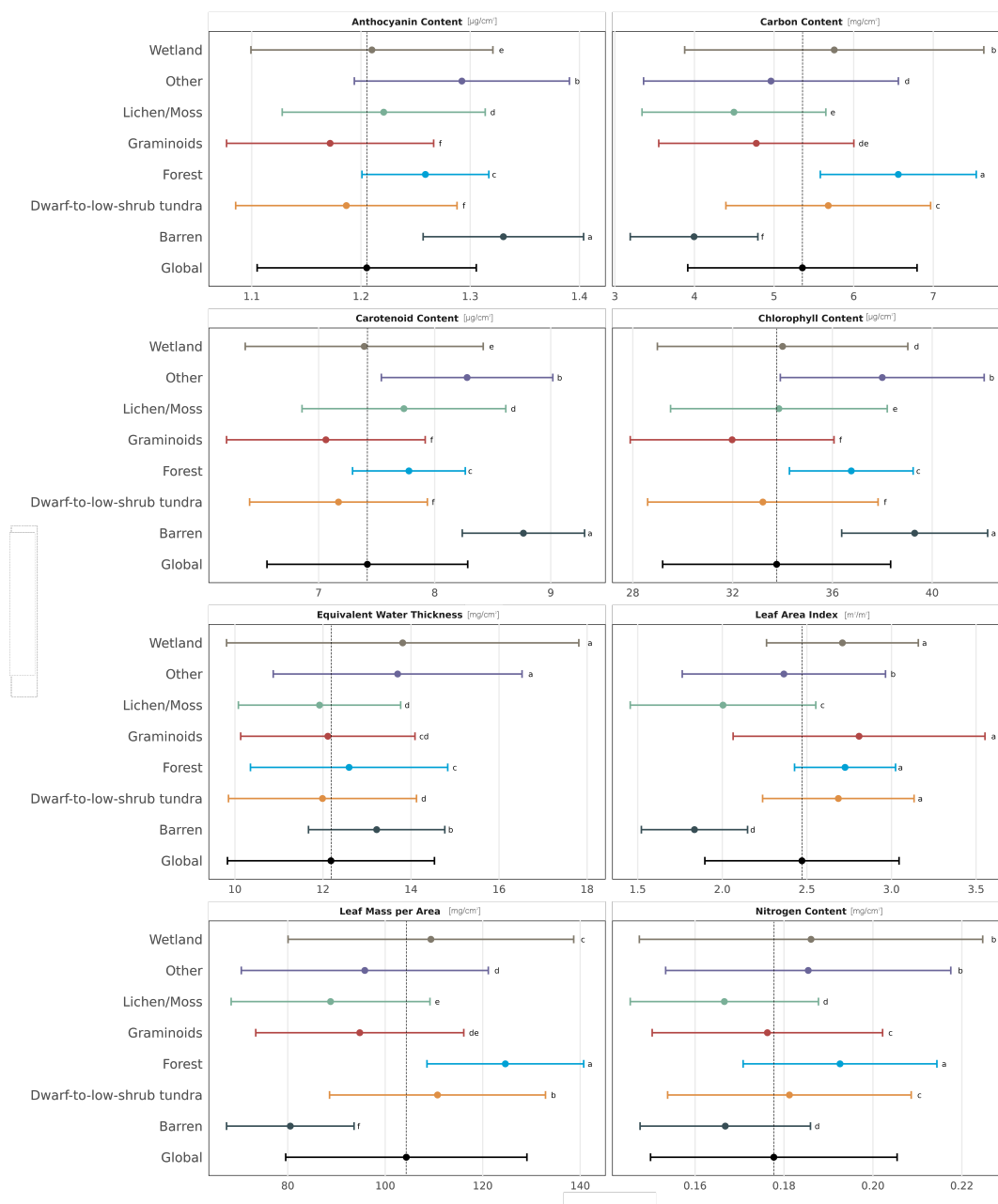


Figure 7. Value ranges of eight selected EnMAP-derived traits from different tundra types (based on CALU map) compared to the trait range across the whole tundra biome ("Global"). Calculations are based on trait data extracted from 10,000 randomly selected pixels per EnMAP scene after masking water and permanent ice/snow. Dots show the mean trait value per CALU type, horizontal lines represent the standard deviation across all pixels, dashed lines show the global mean for orientation. The letters summarize the results of a Tukey test ($\alpha = 0.05$): groups with different letters are significantly different, and vice versa.

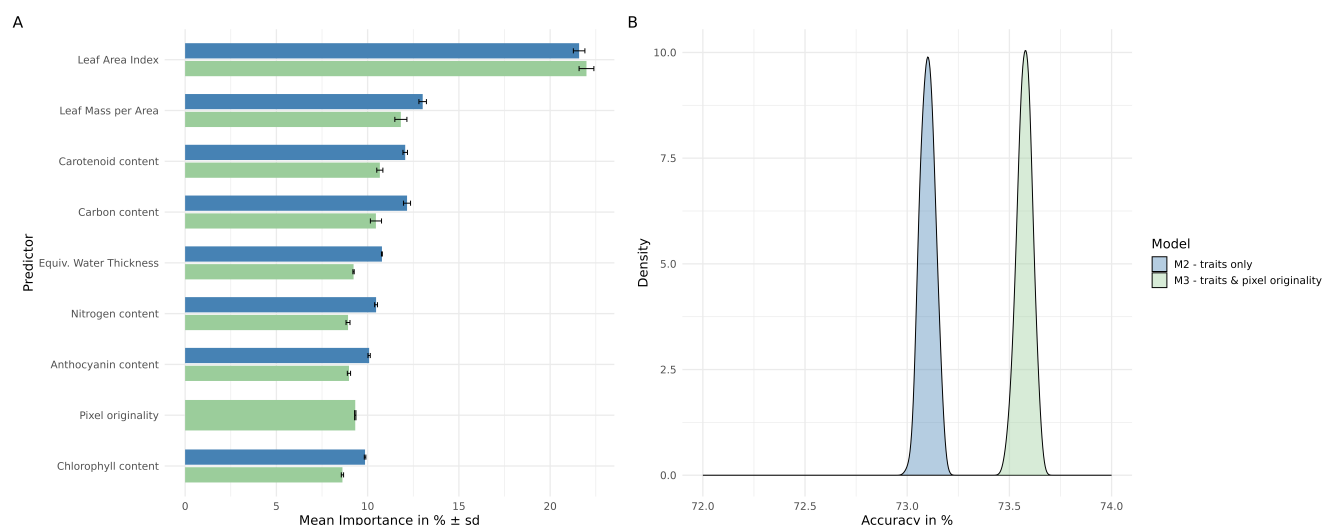


Figure 8. Random Forest classification results across 200 runs for model 1 with EnMAP-derived traits only and model 2 with pixel originality as additional predictor for land cover types (i.e. CALU types). (A) Mean importance $\pm$ sd in % of the individual predictors to the overall mean prediction accuracy of the RF classification. (B) Density distribution of model accuracy across 200 runs for the individual models. Model statistics can be found in table 1.

4.1 Pixel originality as a measure of functional diversity

Pixel originality, derived from the multivariate trait space captured by EnMAP imagery, provided a spatially continuous, classification-free measure of functional uniqueness across Arctic tundra. The RF regression demonstrated that the eight selected traits explained nearly all variation in pixel originality (mean accuracy $\approx 97\%$, $RMSE \approx 0.025$), with LAI emerging as the dominant predictor, followed by LMA, carbon content, and carotenoid content. This indicates that canopy structural and biochemical properties collectively underpin the functional distinctiveness of individual tundra pixels, and that pixel originality is not an independent signal but an integrated expression of the same trait axes that describe vegetation function more broadly. The spatial distribution of pixel originality did not reveal pronounced hotspots of functionally unique tundra within the analysed EnMAP scenes. Instead, spectrally and functionally distinct pixels were clustered around water bodies, rivers, and infrastructural elements, while the vegetated tundra surface showed smooth, continuous gradients of functional uniqueness. This pattern is consistent with the fine-scale functional heterogeneity driven by microtopography and soil moisture that characterises Arctic tundra (Heijmans et al., 2022; Nelson et al., 2022), where transitions between plant communities are gradual rather than abrupt. Recent research underlines this assumption by demonstrating that mainly topography dominates the heterogeneous yet predictable patterns of spatial distribution of Arctic deciduous tall-shrub genera (Yang et al., 2026). From a monitoring perspective, our findings suggest that pixel originality is sensitive to landscape-level functional gradients but may require denser spatial or temporal coverage to resolve discrete diversity hotspots within the vegetated matrix. It is important to note that the presented results are based on single spotlight acquisitions representing unique time points; a more robust assess-



ment of the temporal stability of pixel originality patterns will require multi-temporal data (Mederer et al., 2025b). The concept of pixel originality adapts established principles of functional diversity to the domain of imaging spectroscopy, translating the idea of functional uniqueness from species-level trait databases to spatially continuous remote sensing observations. Whether pixel originality captures comparable ecological information to spectral diversity metrics derived directly from reflectance data (see i.e. Rocchini et al. (2017) or Palmer et al. (2002)) warrants further investigation, but its grounding in ecophysiologicaly meaningful traits rather than raw spectral variation offers a more interpretable basis for ecological assessment.

4.2 Structure of the Arctic trait space

The PCA revealed that two principal components captured $\approx 86\%$ of the total variability in the selected traits, indicating a strong and low-dimensional structure within the EnMAP-derived trait space. PC1 was dominated by traits associated with the leaf economics spectrum (Wright et al., 2004), i.e. LMA, carbon content, nitrogen content, LAI, and EWT, while PC2 reflected pigment-related traits including chlorophyll, carotenoid, and anthocyanin contents. This biaxial organisation aligns with global patterns linking leaf construction costs and resource-use strategies along the first axis (Reich, 2014), and photo-protective and photosynthetic capacity gradients along the second (Díaz et al., 2016), suggesting that EnMAP-derived traits capture ecologically coherent dimensions of plant functional variation even in the spectrally challenging Arctic environment. The continuous but structured density distribution of the trait space suggests smooth ecological transitions rather than discrete functional clusters, a pattern consistent with the fine-grained environmental gradients characteristic of tundra landscapes (Bjorkman et al., 2018; Epstein et al., 2004). The CDA further supported this interpretation: CALU classes formed partly overlapping but structured clouds in canonical trait space, with the first two canonical axes capturing $\approx 75\%$ of between-group variance. Forests showed consistently higher LMA, carbon, and nitrogen content, indicative of conservative resource-use strategies, while graminoids and wetlands exhibited higher LAI and EWT, characteristic of more acquisitive growth forms. The distinctively low pigment concentrations predicted for graminoids likely reflect a retrieval artefact associated with the steep leaf angles of dominant species such as *Eriophorum* spp., which reduce effective canopy exposure towards the sensor rather than indicating genuinely low pigment content (i.e. Sun et al. (2022)). Variability in leaf angles has been shown to significantly influence vegetation indices derived from satellite imagery (Kattenborn et al., 2024) and must be assumed to have similar effects on spectrally-derived pigment concentrations.

The anomalously high pigment and EWT values predicted for barren lands are more difficult to interpret ecologically and may reflect mixed-pixel effects or model extrapolation beyond the training distribution of the CNN (Cherif et al., 2026). The validation of trait predictions against data from the TRY database and literature confirmed a general ecological plausibility of the EnMAP-based estimates at the scene level, strengthening confidence in their use for regional-scale functional characterisation. Nevertheless, the results reveal two fundamental limitations of the study design at this point: (1) the current CNN was not specifically trained on Arctic tundra communities, and the distinctive spectral properties of cryptogams, particularly the high reflectance of lichens and the spectral overlap between mosses and vascular plants (Nelson et al., 2022), likely limit retrieval accuracy for these functionally important groups. Targeted expansion of the training dataset to include Arctic-specific trait-spectra pairs, with particular attention to cryptogam communities, represents a clear priority for improving retrieval per-



295 formance in future applications. (2) The validation of the EnMAP-based traits requires a more in-depth collection and analysis of available trait data from Arctic plant community, favourably based on in-situ measurements from various locations across the circum-Arctic region. At this point, a comparable data collection was not available for this study.

4.3 Trait-based classification of Arctic vegetation types

Both RF classification models achieved comparable mean accuracies of $\approx 73 - 74\%$ across 200 runs, with Cohen's kappa of
300 $\approx 0.52 - 0.53$, demonstrating that EnMAP-derived traits provide substantial discriminatory power for CALU type classification. The marginal improvement gained by adding pixel originality as a predictor in model 3 indicates that trait information alone captures most of the variance relevant for categorical classification, and that pixel originality adds limited independent information in this context. LAI was the dominant predictor in both models, consistent with its role as the primary driver of pixel originality and its strong variation across CALU types. The partial overlap among CALU classes in canonical trait space
305 reflects both genuine ecological gradients and the inherent coarseness of the CALU classification itself. Tundra vegetation forms overlapping functional syndromes shaped by strong environmental filtering and local adaptation (Thomas et al., 2020). At the same time, the broad CALU classes aggregate functionally heterogeneous plant communities that share a dominant growth form but may differ substantially in species composition and physiological strategy. Sub-pixel functional heterogeneity within 30 m EnMAP pixels further complicates class separation, particularly in mosaics of cryptogams and vascular plants.
310 Ground-reference data at fine spatial resolution are therefore necessary to reliably interpret trait-based classification results and to assess the contribution of classification uncertainty in the reference map to apparent model error (Cunliffe et al., 2020). This could be improved by using multi-level data sources (from in-situ trait and spectroscopic measurements to pixel-level trait predictions) and combining them by deep learning models.

4.4 Limitations

315 Several methodological limitations in our study should be acknowledged next to the already mentioned issues. Trait retrieval uncertainties propagate into all downstream analyses, including pixel originality and RF classification, and their cumulative effect on final predictions has not been fully quantified (Cherif et al., 2026). The analyses are based on a limited number of spotlight acquisitions, constraining generalisation across the full spatial and seasonal range of Arctic tundra. The strong seasonality of tundra vegetation affects trait expression throughout the growing season and may systematically influence both
320 trait retrieval and CALU classification outcomes, a question that requires dedicated multi-temporal analysis (Mederer et al., 2025b; Beamish et al., 2016). Finally, the CALU reference map itself carries positional and thematic uncertainty that is difficult to disentangle from model error in the classification results.

4.5 Conclusions

This study demonstrates that plant functional traits retrieved from EnMAP hyperspectral imagery, combined with CNN-based
325 prediction and functional diversity principles, provide a robust and ecologically interpretable framework for characterising



Arctic tundra vegetation at landscape scale. Eight traits spanning the leaf economics spectrum and pigment composition captured the dominant axes of tundra plant functional variation, with two principal components explaining $\approx 86\%$ of total trait variability. This low-dimensional structure reflects the strong environmental filtering that shapes plant strategies across Arctic landscapes and confirms that EnMAP observations resolve ecologically meaningful functional gradients. Pixel originality, introduced here as a spatially continuous measure of functional uniqueness derived from the multivariate trait space, proved to be almost entirely predictable from the selected traits, with LAI, LMA, carbon content, and carotenoid content as the primary drivers. The absence of pronounced functional hotspots within the vegetated tundra surface, and the smooth gradients of pixel originality across the landscape, point to the importance of microtopographic and microclimatic variation in shaping functional diversity at fine spatial scales. These findings highlight both the promise and the current limitations of single-acquisition hyperspectral data for diversity monitoring: pixel originality is ecologically coherent but requires multi-temporal coverage to fully realise its potential for detecting functional change. Trait-based RF classification achieved $\approx 73\%$ accuracy for CALU vegetation types, demonstrating that functional traits alone carry substantial information for distinguishing broad vegetation classes without relying on categorical training labels. The partial but structured separation of CALU classes in canonical trait space underscores that tundra vegetation constitutes a continuous functional landscape rather than a set of discrete communities, a finding with direct implications for how Arctic vegetation change should be monitored and represented. With increasing availability of space-borne hyperspectral data from missions such as EnMAP, PRISMA, and the forthcoming CHIME, trait-based approaches offer scalable tools for tracking ecosystem function and functional diversity across rapidly transforming Arctic landscapes. Future work should prioritise multi-temporal analyses, Arctic-specific CNN training data with improved cryptogam representation, and integration of fine-resolution field measurements to refine trait retrieval and unlock the full potential of functional diversity metrics for supporting conservation and monitoring across the circumpolar region.

Data availability. The EnMAP-based plant functional traits of Arctic tundra communities are available at: <https://doi.org/10.1594/PANGAEA.988012>.

Author contributions. A.L. conducted the formal analysis, data visualization and composed the original draft; B.H. was involved in supervision as well as the review and editing of the manuscript; H.F. provided the original concept and was reviewing and editing the manuscript; all authors developed the methodology for this study.

Competing interests. The authors declare that they have no conflict of interest.



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355 Appendix A

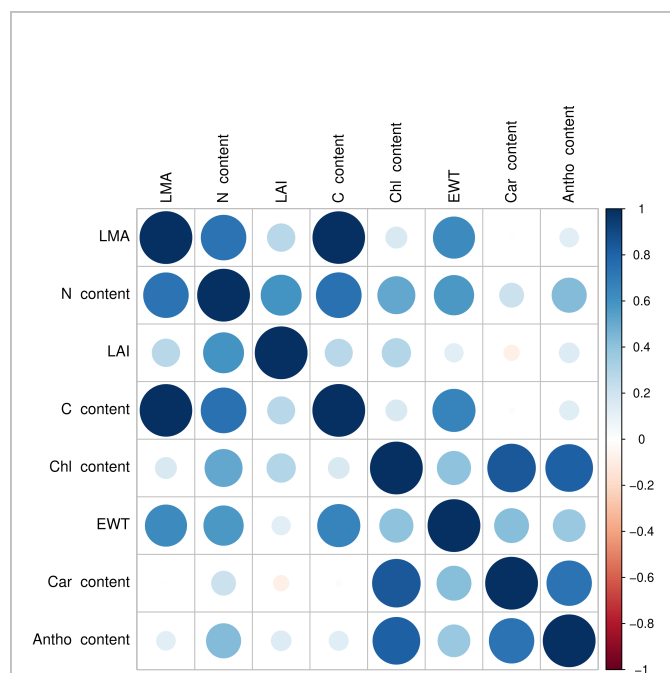


Figure A1. Correlation analysis between shows a strong correlation between some of the eight pre-selected traits. Abbreviations: LMA - leaf mass per area, N - nitrogen, LAI - leaf area index, C - carbon content, Chl - chlorophyll, EWT - equivalent water thickness, Car - carotenoids, Antho - anthocyanins.

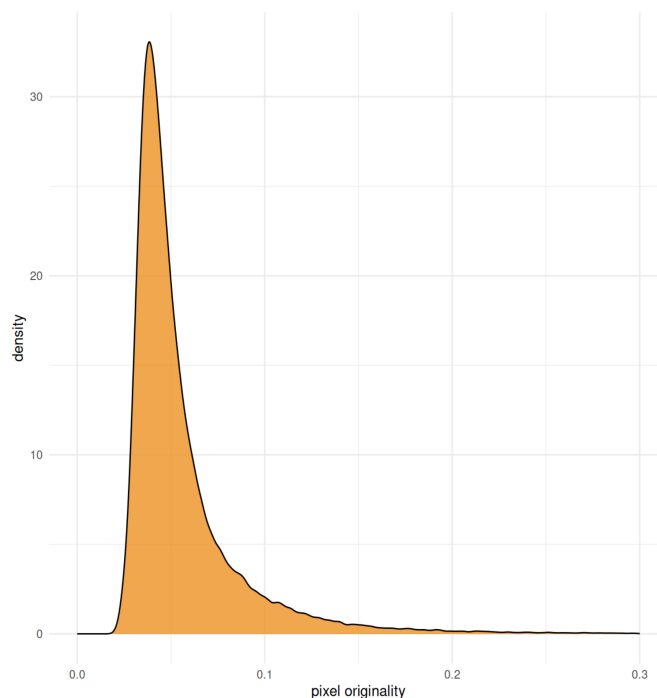


Figure A2. Distribution of pixel originality values calculated for all EnMAP tiles based on a 30-pixel neighbourhood ($k = 30$) in the common spectral PCA trait space. In general, pixel originality has a narrow range with values from 0 to 0.3 (Fig. A2) that are distributed in spatial clusters (see Fig. 4 as a representative example). The majority of pixels fall in the moderate region. Only in few cases high pixel originality has been detected.

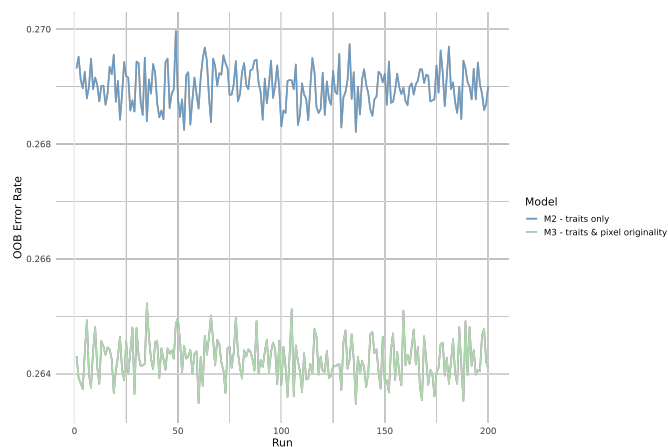


Figure A3. Out-of-bag error rates for RF classification models 2 (traits only) and 3 (traits & pixel originality) across 200 runs.



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