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Title: Ecoregion-wise Fractional Mapping of Tree Functional Composition in Temperate Mixed Forests with Sentinel Data: Integrating Time-Series Spectral and Radar Data

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Abstract

Temperate mixed forest ecosystems are composed of various tree functional types (TFT) that differ in canopy structure, phenology, and physiological response to climate change. An accurate characterization of the composition of these TFTs is important for quantifying land surface carbon, energy, and water cycling, as well as process-based simulation of forest dynamics. However, because the pixel size of satellite imagery is usually larger than temperate tree crowns, it is challenging to untangle the significant pixel-wise signal mixture of TFT across mixed forest regions. Spectral Mixture Analysis (SMA) has been widely used to derive the sub-pixel fractional composition of TFT from satellite imagery, but accounting for the broad spectral variability within TFTs across space and time remains a challenge. Synthetic aperture radar (SAR) can indicate biomass mixture information, but it has not been fully exploited for deriving subpixel TFT composition. To improve TFT composition mapping in mixed forest regions, we developed a Fisher-transformation-based Spectral and Radar Time-series Mixture Analysis (F-SRTMA) framework on Google Earth Engine. The F-SRTMA framework aims to address the space-time TFT variability of satellite signatures based on two modified modules: (1) the use of spectral and radar data with spatial and temporal information, and (2) feature optimization based on Fisher Discriminant Analysis (FDA). We tested the F-SRTMA at three representative temperate mixed landscapes located in the northeastern United States, where time-series Sentinel-1 and -2 data were used to calibrate our F-SRTMA approach. Airborne hyperspectral and LiDAR-derived canopy height data were used to generate ground truth TFT fraction maps for validation. The results demonstrate that (1) compared to the spectral time-series model, the synergy of spectral and radar time-series features yielded higher accuracy at the local sites (R^2 = 0.489 vs. 0.531); (2) optimized feature based on FDA significantly minimized the within-TFT variability while maximized the between-TFT variability, which further improved model generalizability across different landscapes, yielding the highest accuracy with cross-site R^2 increasing from 0.263 to 0.589 and RMSE decreasing from 0.207

to 0.164. Collectively, these results suggest that F-SRTMA can be an accurate and generalizable approach for sub-pixel fraction mapping across temperate mixed landscapes, with the potential to be applied to other mixed forest ecosystems.

Keywords: Tree functional type, spectral mixture analysis, Sentinel, SAR, Spatiotemporal variability, Google Earth Engine

1. Introduction

Temperate mixed forest ecosystems are known for their heterogeneity, and their functioning is significantly regulated by the diversity of plant functions (Anderegg et al., 2018; Espelta et al., 2020; Jung et al., 2021; Van Der Plas et al., 2016). Different groups of tree species often exhibit distinct structural, physiological, and phenological traits that govern many important ecological processes related to plant functions (Díaz & Cabido, 2001; Ustin & Gamon, 2010). Therefore, Tree Functional Types (TFT) have long been a crucial indicator of forest functional diversity. Improving monitoring of TFT composition across environmental gradients is essential for better understanding the dynamics of mixed forests in relation to TFT functioning in carbon, energy, and water cycling, particularly under climate change (Cooley et al., 2022; Han et al., 2022; Poulter et al., 2015).

The global accessibility of spaceborne observations has facilitated large-scale TFT monitoring (Van Cleemput et al., 2021). However, the relatively coarse spatial resolution of publicly available satellite imagery, such as Moderate-resolution Imaging Spectroradiometer (MODIS, 500m), Landsat (30m), and Sentinel-2 (10-20m) (Claverie et al., 2018; Sousa & Davis, 2020), presents challenges for accurately monitoring TFTs due to the widely evident TFT mixture in mixed forest ecosystems. The pixel size of these satellite imagery is typically much larger than the size of temperate tree crowns (e.g., crown diameter oftentimes is smaller than 10m; Wu et al., 2021; Zhao et al., 2022), leading to a pronounced mixed pixel problem where the spectral reflectance of a single pixel originates from a combination of different TFTs (Quintano et al., 2012). As a result, accurate characterization of TFT mixture processes using satellite remote sensing remains challenging, particularly in temperate regions where landscapes often comprise heterogeneous combinations of TFT due to the fragmented land forms and associated complex interactions of vegetation with climate, topography, and disturbance histories over large geographical areas (Box & Fujiwara, 2015).

Generally, spectral mixture algorithms (SMA) have been used to effectively address the mixed pixel problem, in which individual image pixels are explicitly modeled as combinations of pure land cover signals, also known as endmembers (Quintano et al., 2012). However, due to the high inter-class similarity of TFT spectra, the limited number of bands (typically 4~12 bands) in satellite-based multi-spectral imagery constrains the model's unmixing capability (Sousa & Davis, 2020; Q. Wang et al., 2021). The recent advance in satellite remote sensing, such as Sentinel-2 with an increased temporal resolution, has created new opportunities to differentiate tree types by capturing their distinct phenology and physiological seasonal variability (Claverie et al., 2018). This has led to a focus on improving unmixing effectiveness based on the accumulation of dense multi-temporal imagery (spectral time-series mixture analysis, STMA), instead of relying on mono-date imagery (Gómez et al., 2016). The addition of time-series imagery has been demonstrated to significantly improve TFT fractional mapping for different unmixing models, including semi-empirical models (i.e., vegetation indies-based dimidiate pixel model; Gao et al., 2020; Yang et al., 2021) and physics-based models (i.e., linear/non-linear mixture model; Hemmerling et al., 2021; Nill et al., 2022; Schug et al., 2020; Sousa & Davis, 2020; Wang et al., 2021; Zhuo et al., 2022), as well as machine learning (data-driven) models (Bolyn et al., 2022; Okujeni et al., 2021; Senf et al., 2020).

Despite these advances, current techniques for unmixing TFT fractions are exclusively based on spectral-only mixture models. These models can struggle to differentiate spectrally similar vegetation types, or fail to describe TFT variations due to uneven illumination in mountainous regions (Mendes et al., 2019; Waser et al., 2021). To tackle this issue, earlier studies integrated radar imagery with spectral imagery for discrete TFT classifications which resulted in enhanced accuracy (Waser et al., 2021), indicating that this integration could be beneficial in improving the accuracy of TFT mixture analysis. Satellite-based radar data with long wavelength at the centimeter to meter scale display distinct energy intensity that is related to vegetation surface roughness (Giordano et al., 2018; Li et al., 2019) and can be sensitive to seasonal changes in forest structure, such as the defoliation of deciduous trees (Dostálová et al., 2018; Ling et al., 2022; Tanase et al., 2019; Verhegghen et al., 2022). This is because the volume backscattering mechanism is intrinsically linked to canopy structure and biomass dynamics in space and time, with great potential to help improve the spectral-only unmixing models given its ability to estimate plant biophysical properties, such as vegetation biomass or leaf area index (Englhart et al., 2011; Joshi et al., 2015). Similar to spectral mixture analysis, radar-based scattering mixture algorithms are effective in modeling scattering mixture mechanisms from land cover types with different structural attributes (Freeman & Durden, 1998; Giordano et al., 2018; Singh et al., 2019). Such radar-based mixture analyses have been widely used for land cover identification such as snow, ice, or water but have been underexplored for TFT fractional mapping (Arii et al., 2019; Ferguson & Gunn, 2022; Hillebrand et al., 2022; Parida & Mandal, 2020; Tian & Wang, 2022).

To aid in the integration of spectral and radar time-series unmixing, Sentinel-1 is a particularly advantageous satellite source as it provides concurrent time-series radar data with Sentinel-2 multi-spectral data (Malenovský et al., 2012). This combination offers an unprecedented opportunity to assess the individual and combined impacts of spectral and structural information on TFT fractional mapping accuracy. Meanwhile, the growing support of high computational cloud platforms with vast preloaded geospatial datasets and parallel processing capacity, such as Google Earth Engine, offers novel and timely opportunities for multi-source data reconstruction, facilitating large-scale mapping (Gorelick et al., 2017).

When conducting large-scale TFT fractional mapping, the use of time-series and multi-source satellite data can provide more comprehensive information than mono-date or spectral-only data. However, this increased data complexity may introduce insubstantial noise or unrepresentative bands into the unmixing process, which could ultimately affect the model's generalizability across large landscapes. This noise amplification in satellite imagery can be attributed to factors such as cloud and snow cover, shadows, topographic effects, and speckle for radar data, all of which contribute to increased spatial and temporal variability of spectral and/or radar features within TFT and reduce the between-TFT feature contrasts (Q. Wang et al., 2021; F. Zhao et al., 2022; Zhuo et al., 2022). Moreover, the environmental gradient across large scales can also enhance the within-TFT spectral and structural variability, which further reduces the endmember representativeness across space and time (Hemmerling et al., 2021; Sousa & Davis, 2020). To minimize the effect associated with this space-time variability in large-scale unmixing models, researchers often employ either (1) endmember selection to improve endmember library representativeness or (2) band features optimization to improve feature representativeness (Somers et al., 2011). While the former approach solely focuses on accounting for variable mixture conditions with respect to within-TFT variability, the latter approach is more effective because it could suppress the effect from both within-TFT and between-TFT endmember variability (Jin et al., 2010; Liu et al., 2017; Xu et al., 2019). One possible solution to the latter approach is Fisher Discriminant Analysis (FDA; Okada and Tomita, 1985). This kind of supervised data transformation method can convert high-dimensional data inputs into a low-dimensional feature space, where between-class endmember variability is maximized while within-class endmember variability is minimized, thus generating more representative features for complex landscapes. Several recent studies also have demonstrated the great effectiveness of the FDA in resolving the model transferability issue in impermeable surface monitoring (Liu et al., 2017; Ouyang et al., 2022; Xu et al., 2019). However, its ability to improve endmember generalizability in TFT fractional mapping remains underexplored.

The goal of this study is to explore whether the Fisher-transformation-based Spectral and Radar Time-series Mixture Analysis (F-SRTMA) framework can be an effective and accurate way to improve TFT fraction monitoring in temperate mixed forests across large landscapes using Sentinel-1 and -2 time-series imagery. To address the space-time variability of TFT signatures across large heterogeneous landscapes, the F-SRTMA framework utilizes both spatial and temporal information from spectral and radar data and performs an additional feature optimization based on FDA. As our focus, we tested the F-SRTMA at a representative temperate mixed forest ecoregion located in Wisconsin, USA, and aimed to answer the following two questions:

1) To what extent could the integration of spectral and radar time-series imagery improve the accuracy of TFT fractional mapping?

2) Will the embedding of FDA with SRTMA help increase model generalizability across different landscapes?

2. Study sites, materials, and methods

2.1 Study sites

This study focused on the northern upland conifer-hardwood mixed forest ecoregion in Wisconsin, United States, which experiences a continental climate, characterized by long, cold winters and short, warm growing seasons. The mean annual temperature of the ecoregion is approximately 3°C, and the mean annual precipitation is around 800 mm (Mackay et al., 2002). The ecoregion is mosaicked by a dynamic composition of deciduous and evergreen TFT, including deciduous broadleaf hardwoods, evergreen conifers, deciduous conifers, shrubs, and grasses. Based on the differences in leaf habit (evergreen and deciduous) and leaf forms (broadleaf and needle-leaf), we grouped temperate tree species into three types of interest: deciduous broadleaved tree (DBT), evergreen needle-leaved tree (ENT), and deciduous needle-leaved tree (DNT). The remaining land covers were grouped as non-forest (nonF) class and water (W) class.

Within this ecoregion, we selected three sites (Fig. 1) from the National Ecological Observatory

Network (NEON) to evaluate our proposed F-SRTMA method. These sites are the University of Notre Dame Environmental Research Center (UNDE, 46.21° N, 89.51° W), Steigerwaldt (STEI, 45.50°N, 89.50° W), and Chequamegon (CHEQ, 45.81°N, 90.08° W).

We chose these sites for two reasons. First, each of them has unique site characteristics that are representative of the TFT compositional complexity and space-time feature variability across the ecoregion, as they differ considerably in terms of hydrological regime (UNDE), disturbance history (STEI) and topography (CHEQ) according to the NEON site description (https://www/.neonscience.org/field-sites). Specifically, UNDE has many scattered small lakes surrounded by wetlands, with deciduous conifers dominating most of the wetlands. Thus, the background water signal would affect the remotely sensed vegetation signal from space. STEI is a site with intensive human interruption, and the landscape is also composed and contaminated by the remote sensing signals associated with seasonal crops, urban areas, and plantations. CHEQ exhibits relatively complex topographic conditions that affect the illumination and radar backscatter observed from space. As such, these sites and their associated unique site characteristics can serve as an excellent testbed not only for testing the accuracy of our proposed method but also for helping to examine the generalizability issue of the proposed method when applying the method developed at one site to other sites. Secondly, relevant 'ground truth' data to evaluate our remote sensing methods is available at these sites. NEON has conducted annual airborne surveys since 2015, with a very high spatial resolution (1m) airborne hyperspectral and LiDAR imagery. These airborne data would generate accurate classification results, serving as 'ground truth' to evaluate our remote sensing methods in a wall-to-wall manner.

2.2 Materials

We used three types of data in this study: (1) airborne hyperspectral and LiDAR data, (2) Sentinel optical reflectance (Sentinel-2) and radar (Sentinel-1) data, and (3) auxiliary land cover maps (from NEON airborne products and several land cover products).

2.2.1 Airborne hyperspectral imagery and canopy height products

To validate our F-SRTMA method, we used high-resolution (1 m) airborne hyperspectral images and canopy height product (level 1) data acquired from the NEON Airborne Observation Platform. The hyperspectral image data consists of 426 bands ranging from 380 to 2510 nm with a 5 nm spectral resolution. We downloaded the data for the year 2020 from https://data.neonscience.org/ to match with Sentinel satellite imagery. We employed a spectral-spatial residual network (SSRN) deep learning model, specifically a 3D-CNN model (Zhong et al., 2018), to classify each landscape pixel into three tree types (i.e., DBT, DNT, ENT), a non-forested type (nonF) and water (W) type. We chose the SSRN model for its ability to handle high collinearity commonly existing in spectroscopic data and its delivery of state-of-the-art classification performance (Zhong et al., 2018).

There were two steps involved in the SSRN classification. First, to create training and validation data, we manually labeled different land cover types (pixel amount = 1.62×10^6) based on sub-meter historical winter and summer images of the same sites from the ESRI World Imagery Wayback archive (https://livingatlas.arcgis.com/wayback) and Sentinel-2 winter imagery. Second, to train and evaluate the SSRN model, we followed Wong & Yeh (2020) and used a 5-fold cross-validation method with both airborne hyperspectral imagery and canopy height map as model input, where hyperspectral bands were reduced to 10 based on the Minimum Noise Fraction method (MNF, Roger, 1996) to balance the contribution of spectral and structure information to classification model (Fig. S1). The resulting classification had a very high overall accuracy of 0.93 (Table S1), indicating that it can be a reliable benchmark to evaluate satellite-based fraction estimations. To evaluate satellite-derived TFT fractions (at a 10m resolution), we further resampled these 1m resolution classifications and upscaled them to generate a 10m resolution fractional composition of our targeted TFT (i.e., DBT, DNT, ENT, and nonF).

2.2.2 Optical and radar Sentinel data

To test our F-SRTMA method, we used the Sentinel-2 Multispectral Instrument data operated by the European Space Agency. Specifically, the Sentinel-2 level 2A imagery with a 5-day revisit time covering the full year of 2020 was accessed via the Google Earth Engine (GEE). We selected four 10m spectral bands (blue, green, red, and near-infrared bands) and six 20m spectral bands (3 red-edge, 1 near-infrared and 2 short-wave infrared bands) and fused them to a 10m resolution using the nearest neighbour method. To minimize snow and cloud contamination, we first excluded imagery in the snowy season from December to March, as well as imagery with >50% cloud coverage based on the provided CLOUDY_PIXEL_PERCENTAGE parameter. Then, for the remaining imagery, we filtered cloudy pixels based on Sentinel-2 cloud probability bands (i.e., cloud probability>10%), and snow-contaminated pixels based on a thresholding method (i.e., NDSI>0) using Normalized Difference Snow Index (NSDI) following Gascoin et al. (2019). In addition, to minimize solar and sensor view angle effects, we conducted an image-specific Bidirectional Reflectance Distribution Function (BRDF) normalization following the same method as Claverie et al. (2018). We also performed a path length correction algorithm to minimize the topography effects following Yin et al. (2018).

In addition, we accessed Sentinel-1 Level 1 Ground Range Detected (GRD) imagery with a 12-day revisit time covering the full 2020 year via GEE. Sentinel-1 GRD imagery provides backscatter coefficients (σ°) in decibels (dB) based on the Interferometric Wide Swath mode, with a 10m resolution and dual-polarization signals (i.e., vertical transmit-vertical receive, VV, and vertical transmit-horizontal receive, VH). Since the values of backscattering coefficients (σ°_{VV} and σ°_{VH}) typically vary with the incidence angles (ranging from 29° to 46°), we normalized both the σ°_{VV} and σ°_{VH} values to a reference angle of 38° based on a dynamic cosine model (Feng et al., 2021) to reduce this effect. Then, we followed Mullissa et al. (2021) to convert the dB values of σ°_{VV} and σ°_{VH} to linear power unit as $10\sigma^{\circ}/10$ (ranging from 0 to 0.3). To minimize the effect of topography, we utilized the US 10m resolution Digital Elevation Model on GEE for terrain correction, following the method of Vollrath et al. (2020). We also addressed the speckle noises based on a refined-Lee filter with a 5 × 5 pixel window, following Yommy et al. (2015). Although Sentinel-1 data are insensitive to atmospheric conditions, its information can be contaminated by wet underground and snow cover (Dostálová et al., 2018), leading to significant data uncertainty during snowmelt and wet seasons. To eliminate these related extreme values and outliers, we implemented pixel-wise outlier detection based on a 5-year time-series (2018-2022) of two polarizations (VV and VH) in both snow and wet seasons. This method removes observations outside the interquartile range, which is the lower 10% to upper 90% quantiles of the two polarizations, respectively.

2.2.3 Auxiliary land cover data

To evaluate the advantage of fraction mapping on ecoregion-wise TFT, we cross-compared our results with another two discrete classification maps of non-forest type based on two published land cover data: WorldCover 2020 (WC) land cover products with a 10m resolution (Zanaga et al., 2021) and Global Forest Canopy Height 2019 (GCH) with a 30m resolution (Potapov et al., 2021). WC is a land cover product generated based on the Sentinel-2 and Sentinel-1 constellations, with demonstrated high accuracy around the world (Zanaga et al., 2021). The product can be accessed via https://worldcover2020.esa.int/. GCH was developed through an integration of the Global Ecosystem Dynamics Investigation (GEDI) LiDAR data and Landsat analysis-ready time-series data with satisfactory accuracy (Potapov et al., 2021). This product can be accessed via https://glad.umd.edu/dataset/gedi/. We created two binary maps of forest and non-forest based on the 'Tree cover' type of WC and pixels with canopy height >3m from GCH, respectively. We converted these two discrete maps into fraction format by resampling their spatial resolution to 90m. Both maps showed moderately strong correlation with the airborne LiDAR-derived nonF benchmark at three validation sites, and their correlation coefficients were 0.740 and 0.757, respectively. These two forest maps were used as an independent comparison product for our estimated ecoregion-wise forest fraction map (Section 3.4 and 4.3).

2.3 Methods

The F-SRTMA framework includes three main tasks. First, a data fusion approach is conducted to reconstruct spectral-radar time-series (SRT) features that minimize noise over time and improves feature comparability across sites. Second, the endmembers are extracted based on ground reference and a spatial-guided purity metric is used to constrain imagery-wise endmember extraction. Third, FDA is conducted on the extracted endmembers and associated SRT features, aiming to increase the feature contrast (i.e., minimizing intra-TFT variability and maximizing inter-TFT variability) and thus improve the feature representativeness across large regions.

2.3.1 Reconstruction of high-quality SRT features

There are two issues to be addressed in constructing high-quality SRT features for unmixing models: 1) data missing across time-series images associated with cloud/snow contamination, and 2) signal anomalies across the time frame caused by environmental factors such as topography and weather or sensor/preprocessing errors. Existing time-series unmixing models address these issues by using only clear-sky satellite time series (Q. Wang et al., 2021; Zhuo et al., 2022). However, this approach limits model generalizability as clear-sky images collected at a specific combination of time stamps are not always available at different sites or across different years. To make SRT features applicable on a broad scale, we developed a method to gap-fill Sentinel time series data and derive SRT features with even time intervals. Details about the reconstruction method are described below.

To resolve the data missing or anomalies across Sentinel-1 and -2 data time series due to the quality-controlled processes in Section 2.2.2, we applied a pixel-wise gap-filling method on each spectral band with three sub-steps. First, we calculated the median value for each timestamp based on 5-year (2018-2022) Sentinel-1 and -2 data, respectively. Second, for each target pixel in 2020 with a missing value, we gap-filled it with the 5-year median value of the corresponding time stamp if available. Third, if the valid median value was unavailable, we used the monthly average as a reasonable proxy of that pixel in 2020 for gap-filling. To further minimize potential data anomalies, we imposed a 2-order Savitzky–Golay filter following Chen et al. (2004) with a 2-order linear regression smoother at a 7-week window. Lastly, to keep the time interval consistent across different locations, we resampled the Sentinel-1 and -2 data into a monthly median format (Table 1).

2.3.2 Extractions of candidate endmember pixels

The representativeness of endmembers directly affects sub-pixel fractional mapping (Roth et al., 2012). But identifying high-quality endmembers from satellite imagery is especially challenging in temperate forests. This challenge arises from the substantial variability in spatial and temporal signals across and within forest types, driven by phenological diversity and environmental gradients. The spatial-guided purity method has been proven to be effective in estimating pixel purity in diverse landscapes and is applicable due to its unsupervised nature (e.g., Mei et al., 2010; Shi & Wang, 2014). HereThus, a typical spatial-guided metric of morphological eccentricity index (MEI) is deployed to determine the purity from neighborhood information. In detail, the Our endmember extraction process includes four steps:

Step 1 Deriving vegetation specific Principal Component Analysis (PCA) map to enhance the sensitivity of MEI to TFTs. The MEI has demonstrated effectiveness in determining the purity of pixels at the transition region between high albedo land covers (such as urban areas) and low albedo land covers (such as non-urban areas). In the case of temperate forests, where the spectral signatures of different types of vegetation (TFTs) are relatively similar, the MEI index is less sensitive to the mixture among TFTs, considering the large spectral difference between vegetations and non-vegetations. To maximize the feature distance between TFTs, we first removed non-vegetation land covers based on a yearly average NDVI threshold (NDVI > 0.5). Then, we enhanced the contrast between TFT spectra by applying a dimensional reduction approach using PCA.

Step 2 Deriving PCA-MEI map to extract endmember candidates. Following Plaza et al., 2002, for each image pixel, two mathematical morphology operators of dilation and erosion were applied for the first 3 components of the vegetation specific PCA map (Comer, 1999), with dilation selecting the brightest pixel and erosion selecting the darkest pixel in the predefined neighborhood (i.e. N×N window) (Plaza et al., 2002). MEI is calculated as the feature angle distance (FAD, Eqn. 1) between the dilation and the erosion map, with a higher MEI indicating a higher degree of "eccentricity/anomaly" compared to its neighbors.

$$MEI = FAD(A,B) = cos^{-1}\left(\frac{AB}{\|A\|\|B\|}\right) = cos^{-1}\left(\frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i A_i}\sqrt{\sum_{i=1}^{n} B_i B_i}}\right) \tag{1}$$

where A and B denote the 1×3 vector of first three PCA components respectively derived for the dilation and erosion maps. After constructing MEI map, we then created the candidate endmember map using the automated thresholding method, the Otsu method (Otsu, 1979), as suggested by Plaza et al.(2002). The derived threshold T_{MEI} is set to 0.78, and the endmember candidate map can be determined by MEI > T_{MEI}.

Note that the MEI index requires pure and mixed pixels to coexist within neighboring kernels. If the radius is not large enough for covering this "transitioning" from purity to mixtures, such as at homogenous regions, MEI could underestimate the pixel purity (Plaza et al. 2002). Thus, a sensitivity test for the window size was conducted and we found N=20 is the optimal size (Fig. S2). By employing vegetation-specific PCA-MEI to enhance the endmember candidates, we achieved enhanced precision in our model with an overall RMSE decreased from 0.151 to 0.144 when compared to the endmembers obtained directly from the ground truth classification map without the PCA-MEI refining step (Fig. S2).

Step 3: Endmember type determination. Once the candidate endmember pixels were identified, we then overlaid the candidate map of each site with its associated airborne-derived TFT fraction map (Section 2.2.3), by which we assigned each pixel candidate with its corresponding dominant endmember class.

Step 4: Construction of the SRT endmember library. To account for the potential large within-class endmember variability, we followed Xu et al. (2019) and extracted multiple endmembers (sub-class) for each land cover type. The resulting endmember bundle (including K endmembers (sub-classes) for each land cover type) was derived and used as the final endmember library. Specifically, we used the K-means clustering method for automatically identifying sub-classes. Since the number of K could affect the final unmixing results, we conducted a sensitivity analysis to identify the optimal K value. In this analysis, K varied from 1 to 15 with an interval of 2, and the model's performance was assessed using airborne-derived TFT fraction maps. Fig. S3 demonstrates that K=7 and K=1 achieved optimal performance for the model without and with FDA, respectively.

2.3.3 SRT-based mixture analysis (SRTMA)

(1) MESMA

We estimated TFT fractions based on an advanced unmixing model—Multiple Endmember Spectral Mixture Analysis (MESMA) (Roberts et al., 1998), which has been demonstrated to effectively cope with within-class endmember variability (Degerickx et al., 2019). This is because MESMA allows using varied endmember combinations for each pixel instead of a fixed one. This assumption can better cope with reality, where the number of mixture types at a 10m resolution is typically around three, which is much less complex than the number of the entire endmember library (Okujeni et al., 2021). To perform MESMA, we searched for the most representative 3-endmember combinations for each mixed pixel by iterating through all possible 3-endmember combinations from the library. For each iteration of the 3-endmember subset, we used pixel-wise linear spectral mixture analysis (Eqn. 3) to estimate the subpixel abundance.

$$\overrightarrow{Y} = A \cdot \overrightarrow{X} + \vec{e} \tag{2}$$

where $\overrightarrow{Y}$ is $1 \times n$ vector of features for each pixel; $\overrightarrow{X}$ is the $n \times m$ matrix of endmembers; · is dot product; $\vec{e}$ is the systematic error/model residual; n (=number of feature bands; Table 1) and m (=3; endmembers selected from the library) denote the number of feature bands and endmembers, respectively. A is the $1 \times m$ vector of the estimated abundances, which is solved based on a least-squares algorithm (Bro & Jong, 1997), and the derived abundances are subject to the “sum-to-one constraint” and “non-negativity constraint” (Heinz & Chein-I-Chang, 2001). Among the abundances estimated for different endmember subsets, we selected the abundance estimate from the best model with the lowest residual to obtain the final TFT-specific abundance.

(2) FDA-based MESMA

To optimize endmember representativeness, we applied a supervised dimensionality reduction method known as Fisher's discriminant analysis (FDA) to transform the SRT features into Fisher features. The FDA method was chosen for its effectiveness in enhancing the inter-class endmember variability while reducing the intra-class endmember variability, as demonstrated in previous studies (Liu et al., 2017; Ouyang et al., 2022; Xu et al., 2019). Our aim was to address the challenge of low model generalizability across different sites while making little-to-no sacrifice on within-site model accuracy. For detailed information on the mathematics underlying the FDA method, interested readers can refer to Xu et al. (2019).

Here, we implemented FDA using three sub-steps. First, we utilized the previously derived endmember library as input for FDA to identify projection directions that would optimize the distance between data points of different endmember classes when minimizing the distance within each class. This resulted in a Fisher transformation projection vector $V = \{v_1, v_2, \ldots, v_{k-1}\}$, with a dimension of $n\times(k-1)$ (where n is number of the features, k is the number of endmember types and in this study k=5). Second, we transformed the original features into k-1 Fisher features based on projection vector V. By applying this feature dimensional reduction, Eqn. 3 was converted into Eqn. 4, as shown below.

$$V \cdot \overrightarrow{Y} = A \cdot V \cdot \overrightarrow{X} + \vec{e} \tag{4}$$

where V refers to the FDA projection vector, while A, $\overrightarrow{X}$ and $\vec{Y}$ are the same as those shown in Eqn. 3. · is dot product. In a pixel-wise iterative procedure, we searched for the best estimate in the yielded Fisher feature space. By solving abundance matrix A in Eqn. 4 for each of the 3-endmember combinations following Heinz & Chein-I-Chang (2001), we selected the combination with the lowest model residual $\vec{e}$ to determine the corresponding land cover types and their abundance. This process was conducted on a pixel basis for the whole image.

2.3.4 Analytical experiments and model evaluations

To examine the accuracy and cross-site generalizability of F-SRTMA, we conducted four analyses. The first analysis aimed to assess the separate and joint contributions of spectral, radar, and temporal features to the accuracy of TFT fractional mapping. We compared the MESMA models with different features as model inputs, including 1) Spectrum of the annual median (mono-S), 2) Radar Time-series (RT), 3) Spectral Time-series (ST), 4) Spectral and Radar Time-series (SRT), and 5) Fisher features derived from Spectral and Radar Time-series (FDA-SRT). To evaluate inter- and intra-site performance with comparable settings, for each site, we conducted an independent 3-fold spatial cross-validation. For this, we divided each site into 2km×2km sub-tiles, which were split into 3 groups, with each group being used iteratively for unmixing and validation while the other 2 groups were reserved for endmember extraction.

The second analysis aimed to examine whether the FDA method suppresses feature space-time variability and improves cross-site model generalizability. For this purpose, we first compared the within-class and between-class feature variability within the FDA space and principal component analysis (PCA) space. Then, we compared two modelling scenarios with *vs.* without FDA for different feature combinations.

The third analysis aimed to evaluate the model's generalizability across large landscapes. We designed a non-local-based endmember scenario, where a site-specific endmember library was first extracted and then applied respectively to the other two sites. We conducted non-local endmember scenarios for different feature combinations across three sites. Then we compared the accuracy of the non-local scenarios with the local-based endmember scenarios in the second analysis.

The fourth analysis aimed to upscale the F-SRTMA for TFT fractional mapping across the entire ecoregion in Fig. 1. We coded our F-SRTMA method on GEE, from which we derived the ecoregion map of TFT fractions. To illustrate the necessity of fractional mapping in heterogeneous landscapes, we then cross-compared the derived non-forested (nonF) fractions with two state-of-the-art non-forest products (WC and GCH) on the ecoregion scale.

We used benchmark data from the airborne-derived TFT fraction map for validation. We used four common validation metrics in unmixing studies (Nill et al., 2022; Powell et al., 2007;

Senf et al., 2020): Root Mean Square Error (RMSE), coefficient of determination (R^2), and slope and intercept of a regression line, where RMSE quantifies the absolute model error, R^2 quantifies the goodness-of-fit in models, and slope and intercept indicate the model systematic error and bias. The validation data were evenly sampled from low to high fraction intervals (i.e., 0.1–0.2, 0.2–0.3, ...,0.9–1.0), where each fraction interval has 100 randomly sampled pixels. Note that potential geolocation errors in Sentinel imagery can add up to > 12m and lead to noise and associated uncertainties when validating, especially for those TFTs with rare-to-subdominant abundance (Schubert et al., 2017). To minimize uncertainties from potential geolocation errors across different datasets, we followed J. Wang et al. (2023) and resampled all the land cover maps from the original 10m resolution to a coarser spatial resolution. We further conducted a sensitivity analysis on the evaluation accuracy across a wide range of spatial resolutions from 30m to 110m with an interval of 20m. Our findings indicate that a spatial resolution of 90 m is optimal as it minimizes geolocation errors between different data sources (Fig. S4).

3. Results

3.1 Temporal patterns of TFT endmembers

By analyzing endmember patterns (Fig. 2), it is noted that different bands of Sentinel-2 sensor can capture various ecological dynamics, including seasonal changes in leaf color, quantity, and potential leaf biochemistry. For instance, broadleaf forests generally present higher concentrations of chlorophyll (refs), which leads to a higher reflectance in the near-infrared band and lower reflectance in the red band compared to needleleaf forests. Conifer foliage often exhibits significant clumping effects (refs), leading to a more aggregated arrangement compared to the dispersed foliage arrangement found in broadleaf forests. As a result, ENT and DNT exhibit lower overall light reflectance in comparison to deciduous broadleaf trees (DBT).In terms of phenology, deciduous broadleaf trees (DBT) and DNT demonstrate significant reflectance in the visible and short-wave infrared bands, indicating changes in leaf color to yellow and leaf drop. However, these measurements might be contaminated by the ground reflectance. ENT reflectance also exhibits relative seasonality across most bands, which can be partly attributed to the Bidirectional Reflectance Distribution Function (BRDF) effect that amplifies the seasonal variation in conjunction with the solar angle changes. The phenology patterns observed in the red-edge and near-infrared bands (B6-B8A) are almost similar, implying a strong relationship between these bands and capturing changes related to vegetation growth, health, and senescence. The reflectance of TFTs endmembers shows significant overlaps with that of non-F type, which suggests that distinguishing TFTs solely based on spectral information is challenging due to their similar spectral characteristics.

Regarding the SAR patterns, our observations indicate that both VV and VH polarizations are sensitive to surface structures (Figs. 2k and 2l). The non-F type in SAR data is more separable compared to the Senitinel-2 bands (Figs. 2a-2h). Notably, conifer trees display higher canopy (volume) scattering value than broadleaf trees in both VV and VH bands. Additionally, the volume scattering between DNT and ENT are identical, with DNT showing higher values than ENT. This reflects the fact that DNT typically exhibits a higher tree density compared to ENT. DBT demonstrates pronounced seasonal patterns in VH bands compared to DNT. On the other hand, TFTs show fewer seasonal patterns in VV values compared to VHs. This distinction can be attributed to VH's heightened sensitivity to randomly oriented structures, such as tree canopies, whereas VV is more responsive to linearly oriented structures like surface and trunks (refs).

3.2 Evaluating the effectiveness of SRT features for TFT fractional mapping

We investigated the performance of different feature combinations on sub-pixel TFT fractional mapping. Among the four non-FDA feature scenarios examined (Table 2), SRT features yielded the highest overall accuracy (RMSE=0.176, R^2=0.531) across all study sites, followed by ST

(RMSE=0.180, R^2=0.489), RT (RMSE=0.210, R^2=-0.251), and mono-S (RMSE=0.222, R^2=0.074). We found that the contribution of different SRT features to unmixing is different at the TFT level (DBT, DNT, and ENT). For instance, radar time-series data were found to be highly capable of identifying the cover of DBT (RMSE=0.192, R^2=0.378), but less efficient for differentiating DNT and ENT (RSME=0.199 and 0.235; R^2=-0.055 and -1.569, Table 2). Compared to radar time series, spectral time series were more effective at estimating ENT than DNT (RMSE=0.185 and 0.161; R^2 = 0.234 and 0.649, Table 2). The combined use of spectral and radar time series (SRT) resulted in a further increase in overall accuracy relative to ST features, as indicated by an improvement in R^2 from 0.489 to 0.531, and a decreased RMSE from 0.180 to 0.176 across all three sites, particularly for DNT (R^2 increased from 0.234 to 0.396, RMSE decreased from 0.185 to 0.178), but with an exception for ENT (R^2 decreased from 0.649 to 0.625). Compared to TFT fractional cover, the mapping accuracy of nonF cover decreased with the integration of spectral and radar features (RMSE=0.189 vs. 0.193 for ST and SRT features, Table 2. This suggested that constructed SRT endmember library was not robust against the significantly high within-nonF variability.

3.3 Evaluating the effectiveness of FDA features

To evaluate the effectiveness of FDA in optimizing the endmember variability between different TFTs, we compared the dimensional reduction of SRT features base on FDA with PCA (Figs. 3). Our findings revealed a significant decrease in the similarity among different endmembers when using FDA, as compared to PCA. This suggests that FDA features offer improved representativeness (Fig. 3a and c). Specifically, when comparing the first four features of PCA and FDA results (Figs. 3b and 3d), we found that PCA features of the nonF type exhibited the highest within-class variability and the largest overlap regions with all three TFTs. In contrast, FDA features of the nonF type displayed less variability and a larger distance to TFTs. Additionally, ENT and DNT were highly similar in the PCA features, while were distinct in the FDA features (Figs. 3b and 3d). This optimization for within- and between-class variability explains the accuracy increment in models using FDA-SRT features compared with SRT features in the within-site experiments (RMSE = 0.176 vs. 0.150, and R^2 = 0.668 vs. 0.531, Table 2). Notably, the nonF type experienced the most significant decrease of with-class variability, resulting in the highest increase in R^2 of 0.199, followed by DNT with an increase of 0.179, DBT with an increase of 0.161, and ENT with a marginal increase of 0.001 (Table 2).Overall, the FDA analysis reduced the original feature dimensions to a much smaller dimension (*n*=180 vs. 4), resulting in improved fractional mapping accuracy and computational efficiency. Notably, the FDA features with reduced within-class variability enabled the model to use only one endmember for each land type to accomplish high accuracy, compared to the non-FDA models that usually require a more abundant endmember library to represent large variability across landscapes (Fig. S3).

3.4 Evaluating the cross-site model generalizability

We aimed to investigate whether the utilization of different feature scenarios could improve the representation of cross-site endmembers, thereby improving the model generalizability (Table 2 vs. Table 3). In two ST-only feature scenarios, we observed a significant reduction of the overall accuracy compared to the within-site models (R^2 = -0.525 vs. 0.489, RMSE = 0.222 vs.0.180). This indicates that models using ST features lack generalizability when applied to large landscapes. ST features can adequately simulate the DBT and ENT in a ok matter (R^2 = 0.307 and 0.424, RMSE=0.127 and 0.168), but poorly represent the DNT and nonF (R^2 = -3.08 and 0.171, RMSE=0.274 and 0.231). The FDA transforming can increase ST model generalizability, although it falls short of achieving cross-site performance comparable to the within-site level. Despite the transforming of ST to FDA-ST features, the large cross-site variability still negatively affects the DNT unmixing (R^2 = -1.106, RMSE=0.195). Moreover, the class-wise accuracy is unstable (R^2 = -1.106-0.769). In this regard, the addition of radar time-series data into the SRT features proves critical as it significantly improves the DNT accuracy ($R^2 = 0.187$, RMSE = 0.195) and the FDA transformation further improved the DNT accuracy ($R^2 = 0.341$, RMSE = 0.187).

We next explored the potential benefits of incorporating FDA embedding to mitigate the adverse effects caused by significant variations in space-time features within the same class, and thus increase the cross-site model generalizability (Fig. 4). The SRT endmembers showed low cross-site generalizability because the accuracy for local and non-local scenarios exhibited poor alignment , where the largest differences in accuracy were observed for nonF type (R^2=0.134 vs. 0.660, RMSE = 0.235 vs. 0.163). In contrast, models of SRT features consistently outperformed ST-only models, and the accuracy for both with-in and cross-site evaluations was more comparable (R^2 = 0.589 vs. 0.668, RMSE =0.164 vs. 0.150, Table 3). This demonstrated that the feature addition on its own is not sufficient to improve model cross-site generalizability, especially for land cover types that exhibit large space-time feature variability. The use of FDA-SRT endmembers resolved this deficiency and generated similarly high accuracy under both local and non-local scenarios (Figs. 4). We observed that the combination with FDA analysis can lead to a substantially improved accuracy for nonF type ($RMSE_{non\text{-}local}$ = 0.235 vs. 0.163, $R^2_{non\text{-}local}$=0.134 vs 0.660). .

When examining the scatter plots (Fig. 5) and considering the fitting red line, the non-FDA model tends to overestimate DBT and DNT at where they are fragmented (fraction < 0.4 for SRTMA and fraction<0.3 for F-SRTMA) while underestimating the fractions at where they are dominated. Similarly, for ENT and nonF, the models tend to underestimate their fractions across the fraction gradient. However, the scatter plots show a significant decrease in the bias when incorporated FDA into SRTMA model.3.5 Ecoregion-wise mapping and cross-comparison with discrete non-forest products

To demonstrate the effectiveness of the F-SRTMA approach for mapping forest/non-forest fractions across large and diverse landscapes, we conducted a cross-comparison of the nonF fractions on a 90m patch level derived using the F-SRTMA approach with two nonF classification products (WC and GCH). The comparison revealed a strong correlation between the fraction maps derived from F-SRTMA and those from the other two products across the ecoregion (0.740 for WC and 0.759 for GCH). However, upon closer examination of the spatial patterns, we found that the two discrete maps tended to underestimate non-forested extents compared to our nonF fraction map, especially in areas where the physical sizes of ground objects (i.e., roads, streams, canopy gaps) are smaller than those of satellite image pixels (Fig. 8). In contrast, our proposed F-SRTMA approach was able to accurately capture these fine-scale land cover types, providing more precise sub-pixel level information.

4. Discussion

Mapping TFT fractions at a large scale is critical to understanding the composition and functional response of temperate mixed forests to changing climates. However, it remains challenging for satellite-based approaches to achieve high accuracy and cross-site generalizability. In our study, we proposed the F-SRTMA framework, which addresses these challenges with two novel aspects: (1) higher accuracy of TFT fractional mapping achieved by assimilating more feature dimensions (i.e., spectral, radar and temporal; SRT) compared to the conventional SMA and STMA methods that rely on the spectral features only, and (2) improved cross-site model generalizability achieved by further integrating FDA with SRT features.

4.1 Effectiveness of the F-SRTMA framework in advancing the TFT fractional mapping

Distinct and representative features are critical for accurate spectral unmixing analysis and thus TFT fractional mapping. We found that the combined use of time-series spectral reflectance and radar signatures could be a way to improve unmixing accuracy. First, the inclusion of time-series spectral information provided a more comprehensive representation of TFT ecological dynamics, such as seasonal displays in leaf color, quantity and potential leaf biochemistry (J. Wu et al., 2018; S. Wu et al., 2021; X. Yang et al., 2014). In contrast, limited spectral information inherent in single multi-spectral imagery (Q. Wang et al., 2021) will typically lead to the "spectra mimicking" issue where different TFTs may sometimes display similar spectrums (Adams & Gillespie, 2006). Thus, compared to mono-date spectral mixture analysis models, time-series spectral information increased the separability among different TFTs and yielded superior TFT fractional mapping results (Table 2). Although our study did not specifically explore ENT in the model, EBT vs. ENT could present similar "spectra mimicking" issue and is commonly observed in lower latitude regions. The demonstrated canopy structure for broadleaf vs. needleleaf trees inferred from SAR data could potentially aid in distinguishing with different broadleaf and conifer trees coexistence (i.e. EBT vs ENT; DBT vs DNT) in future study regions.

Second, our study demonstrated that time-series radar information further enhanced the separability among TFTs to other vegetations, particularly for those with considerable differences in canopy structure (e.g., ENT *vs.* DBT, tree *vs.* grass, Figs. 2k and 2l). Specifically, we observed that the endmember candidates of the nonF type exhibited significant spectral band overlap with the DNT but were more distinguishable in the VV and VH bands (Fig.2). Thus, the RT features significantly enhanced their differentiation and resolved the "spectra mimicking" effects, The DBT displayed a distinct temporal pattern in the ST features (especially in red-edge to near infrared bands), which means a less spectra mimicking effect. Consequently, incorporating the RT features did not show significant compliment on its differentiation.Notably, our study examined radar backscatter time-series signals for unmixing models for the first time. The clear physical meaning of backscatter signals is comparable to the philosophy of time-series spectral mixture (Arii et al., 2019), allowing radar data to simulate the fraction mixture of "flat" and "rough" surface dynamics (Waser et al., 2021). For instance, backscatters from broadleaved trees exhibited higher values in both polarizations during the leaf-off period compared to the leaf-on period (Reiche et al., 2018; Tanase et al., 2019), which is useful in distinguishing tall trees from low vegetation such as shrubs and grass. However, our findings indicate that deciduous conifer structural seasonality is less pronounced compared to DBT (Figs. 2k, 2l). This inefficiency in identifying conifers' structure using radar data has been previously demonstrated in the literature (Ferrazzoli & Guerriero, 1995; Li et al., 2019). Especially for the C-band radar data of Sentinel-1, the short wavelengths (5.547 cm) makes it difficult to penetrate the tree canopy and results in relatively lower separability between different tree types (Ling et al., 2022). As a result,, the conifers (ENT and DNT) endmembers of VV and VH band showed significant overlap (Figs. 2k, 2l). Additionally, due to the weaker penetration capability of C-band compared to P- and L- band data, it is demonstrated that the C-band multi-scattering effects is weaker in forest regions, as the canopy scattering is dominant while trunk signals for the C-band are close to the noise floor while ground signals are not significant in forest (Freeman & Durden, 1998).

The major concerns of these SAR-based linear models are that their non-linear mixture relationship is significantly stronger compared to optical data owing to the multi-scattering effects from the penetration of canopy. This also explains why the improvement for non-FDA models of SRT over ST is somehow marginal or even negative. Considering this drawback, our model only used SAR data as a complementary source for the optical information ands proved that there is a positive contribution of SAR data to overall model performance for most TFTs (Table 2). Therefore, we demonstrated that, by incorporating FDA, structural dynamics can play a unique role in complementary the optical data for distinguishing TFTs.

To further quantify the multi-scattering effects on linear mixture models, we analyzed their residuals in the spatial map (Fig. S6). We found the multi-scattering energy did lead to a higher model residual, with a small residual difference between F-SRTMA vs. F-STMA (Fig. S6a). We showcased three examples of high residual regions for RTMA model. Example 1 represents that model failed to capture the ground-trunk scattering at forest boundary; example 2 represents the surface scattering from the wetland; and example 3 represents the canopy (volume) scattering from the dense needle evergreen trees). Despite the high residuals, the RTMA-based fraction map still shows a high spatial consistency with ground truth map (Figs. S6c and S6d), which indicates that these residuals do not significantly affect the estimated TFT fractions. Our study provides valuable insights into the efficiency of radar time-series in distinguishing between different tree types, which can help improve the accuracy of TFT fractional mapping.

4.2 Enhanced model generalizability for broader-scale TFT fractional mapping

The lack of generalizability can limit the usefulness of the model for large-scale mapping applications, where accurate and consistent results across different areas and time are critical. To address this issue, we integrated FDA with SRT features to improve the representativeness of the TFT endmember library across complex vegetation landscapes. However, we observed that the localized library of SRT endmembers was not as effective when mapping other non-local landscapes (Table 3). This observation can be attributed to two reasons. First, the inclusion of higher feature dimensions often comes with a cost, as it will bring certain features that show high sensitivity to ambient (e.g., residual cloud/aerosol contamination, snow effect, topography effect) and results in a much lower signal-to-noise ratio (Gómez et al., 2016; Zhang et al., 2019). For example, the low accuracy of nonF type is likely due to the high within-class variability associated with diverse land materials and ambience noises across space and time, which is difficult to capture with the constructed endmember library. This high variability is evident in the PCA space of pure pixels, which shows that nonF has significantly larger within-class variability compared to other land classes of interest (Figs. 3a and 3b). The use of FDA tended to help suppress the impact associated with these ambient noises through feature dimension reduction, leading to improved TFT fractional mapping, especially for those TFTs with rare-to-subdominant abundance (i.e., DNT and nonF; Fig. 3, Table 3).

The second reason is that increased feature dimensions often lead to much higher within-class feature variability and reduced feature contrast between classes (Figs. 3a-3d), making the extracted endmember library less representative and generalizable when being extended to large, divergent landscapes. Specifically, for site UNDE, DNT and nonF are strongly influenced by the background signal from diverse wetland habitats (water and moist soil), which differs from the other two sites. For the CHEQ site, the DNT and nonF are fragmented with small coverage and affected by local topographic conditions, indicating that the endmember library extracted from this site could be biased and less representative of other locations. The heatmap illustrated that endmembers extracted from the CHEQ site are less representative in the cross-site test compared to the other two sites for DBT, with the R^2 value of 0.53 and 0.49 against 0.73. For DNT, the R^2 of cross-site models were lowest while RMSE were highest and showed the largest difference from the within-site results, owing to the difficulties to account for its complex habitat environment across landscapes (i.e., wetland and pond). Because FDA-derived features minimize the within-TFT variability while maximizing the between-TFT variability, we thus clearly observed a lower ambiguity between TFTs in FDA features (Figs. 3a-3b) compared to original features (Figs. 3c-3d). Collectively, by integrating FDA with the SRTMA model, we tackled the above issues, making the FDA-SRT features more representative of broader landscapes. The consistent effectiveness of our proposed F-SRTMA approach in local and non-local scenarios (Figs. 4) suggests that the FDA method is efficient in handling endmember candidates belonging to diverse and heterogeneous landscapes. This indicates that the approach has high potential for application to other satellites with comparable spatial resolution ranges such as Landsat of 30m and PlanetScope of 3m (J. Wang et al., 2023).

Our validation approach differs from most previous unmixing studies in terms of both the benchmark data used (i.e., fraction maps across divergent landscapes) and the validation strategy employed (i.e., independent K-fold evaluation). Previous studies commonly used fraction validation datasets that only cover a small fraction of research regions, such as phonecam imagery (Sousa & Davis, 2020) or manual interpretation/field survey plots (Bolyn et al., 2022; Nill et al., 2022; Okujeni et al., 2021), given the difficulty to generate finer-scale benchmark dataset covering large landscapes. Our benchmark data, which covers 392 km^2 and spans a distance of 100 km between sites, is crucial for evaluating the generalizability of the model across landscapes with diverse TFT compositions and high spatial heterogeneity. This provides an improved assessment of the model's predictive capabilities under different scenarios. Additionally, the independent K-fold accuracy assessment is vital for the non-biased validation of fraction estimations, but it was rarely used among the previous TFT fraction validation exercises. In this regard, our study provides a more rigorous and comparable accuracy assessment of our proposed F-SRTMA framework.

Our F-SRTMA framework embeds three independent and easy-to-implement modules (i.e., SRT feature reconstruction, spatial-guided endmember extraction, and FDA features) into the SMA framework, which implies that our modeling framework can be largely adapted to other novel endmember extraction/unmixing algorithms or future advanced remote sensing datasets. Specifically, our locally extracted endmembers with time-series features are tractable for any location or multi-year estimations. This is because the reconstructed SRT features in monthly format can counteract the influence of various observational dates across large landscapes and different years, in contrast to other time-series mixture analysis models that only use good-quality satellite imagery with varying acquisition dates across landscapes or years (Hemmerling et al., 2021; Okujeni et al., 2021; Q. Wang et al., 2021). Moreover, the whole framework was developed on GEE, making it easy to be extended to other remote sensing datasets or locations.

4.3 Ecological Implications

The derived fractional TFT compositions provide an important dataset for interpreting the processes underlying the regulation of ecosystem multi-functionality in this ecoregion. Previous studies have shown that the magnitude and directional change of understory vegetation composition and density with climate change are largely mediated by the upper canopies of broadleaved *vs*. conifer TFTs due to their distinct canopy structures (Cook, 2015; Sonnier et al., 2020; Wiegmann & Waller, 2006). In addition, due to the fundamental differences in plant phenological and physiological characteristics among different TFTs, fractional TFT compositions improve understanding and modelling of their impacts on ecosystem phenology (Smith & Keenan, 2020) light/water use efficiency (Ahl et al., 2004; Murphy et al., 2022), as well as water/carbon flux seasonality (Krasnova et al., 2019; Mackay et al., 2002). Since these studies were mainly based on site/plot-level datasets, our ecoregion-wise TFT fraction map provides a way to scale up this site-level knowledge.

Furthermore, the generated dataset provides a unique opportunity to understand the overall picture of multifaceted TFT assemblages in the upland mixed forest ecoregion and to reveal proximate environmental drivers underlying the observed patterns (Fig. 7). Generally, DBT was found to be the dominant TFT in this ecoregion, while DNT was found to be the most fragmented across the entire ecoregion (NatureServe, 2018). The fractional TFT distribution along elevational gradients supports the topographic niche hypothesis that has often been hypothesized for explaining the biogeography of TFT distributions (Figs. 7b and 7c; Bai et al., 2015). The shared and separated elevational niches among different TFTs indicate that DNT (mostly fir (Abies spp.) and tamarack (Larix spp.)) are well mixed with the ENT (typically including pine (Pinus spp.) and spruce (Picea spp.)) in lowland floodplains (i.e., by lakes or wetlands), while DBT becomes dominant in elevated and steeper regions (Fig. 7b). Notably, our estimates of the area-based distribution of TFTs are closely related to local species-level observations that DNT mainly grows in warmer and wetter areas while DBT can survive in colder and drier environments (Mamet et al., 2019; Neves et al., 2021; Waller et al., 2013). The results reinforce the finding that the TFT mixture is notably evident in temperate regions, where TFT fractions often exhibit significant variations across environmental gradients. These variations can be attributed to a range of factors, including climatic and topographic conditions, as well as intricate complex interactions between vegetation, climate, topography, and disturbance histories (Echeverría-Londoño et al., 2018; Swenson et al., 2012; Hansen et al., 2013).

Our results demonstrate that subpixel-level fractions are more efficient than discrete classes for characterizing forest density and volume. They show a higher accuracy with airborne LiDAR-based canopy height results than the other two state-of-the-art forested products (Fig. 8). Forest fractions, including fractions of forest gaps and forest edges, can be used to infer the density/volume of the forest fragmentation level, an essential metric for studying forest multi-functionality, such as carbon cycling (Krasnova et al., 2019; Moore et al., 2016), forest mortality (Barton et al., 2017), drought and other stress responses (Gleason et al., 2017). However, this relevant information was not well depicted for the temperate mixed forest ecosystem because the size of canopy gaps among the sparse stands is often smaller than the area of a satellite image pixel, as shown in the examples in Fig. 8. The F-SRTMA framework for subpixel abundance mapping is thus advantageous for characterizing such fragmented forest compositions in both mixed and open-canopy forest ecosystems.

4.4 Limitation and future perspective

Our study has three main limitations, and further efforts could enhance TFT fractional mapping. First, using land cover data to determine TFT endmember types (step 2 in Section 2.3.2) might limit its applications in areas where land cover reference is unavailable. Additionally, it is important to note that the accuracy of classification maps may not always be sufficient when utilizing these methods, which may necessitate the refinement of endmembers. The spatial-spectral-based refinement method, such as MEI used in this study, may only selects one dominant type of pure pixel per kernel neighborhood, potentially leading to the loss of important endmembers in certain situations, especially the land type with small coverage (i.e., buildings and roads) (Plaza et al. 2002). Thus, instead of relying solely on specific reference maps, we suggest determining land cover automatically using empirical constraints, such as vegetation indie-based thresholds (J. Wang et al., 2023), or doing it manually through visual interpretation (Nill et al., 2022; Ouyang et al., 2022; Schug et al., 2020). As more high-spatial resolution reference datasets are becoming available across continents, such as the IDtrees NIST NEON submeter airborne classification map (Weinstein et al., 2019), or forest *in-situ* survey datasets such as LUCAS (D'Andrimont et al., 2020) and SiDroForest (van Geffen et al., 2022), we anticipate that these restrictions can be alleviated in the future.

Second, the shallow penetration depth (around 5 cm) of Sentinel-1 C-band data limits its sensitivity of structure detection, as mentioned in Section 4.1. To address this issue, future studies are suggested to use longer wavelength bands of SAR data, such as L-band (with a wavelength of 15–30 cm) and P-band (with a wavelength of 30-100cm). These longer wavelength bands offer a significantly enhanced ability to penetrate deeper into forest canopies and provide multi-layer structural information (Carreiras et al., 2017; Englhart et al., 2011). Ultimately, this could increase the signal-to-noise ratio of the extracted forest structure information (Li et al., 2019). Examples of suitable SAR data for this purpose include PALSAR (Rosenqvist et al., 2007) and BIOMASS (Sedehi et al., 2021).

Third, our proposed F-SRTMA framework exhibits high scalability and is designed for integration with various data sources or algorithms in the future. Although our study employed the F-SRTMA framework based on Sentinel -1 and -2 imagery, it can be extended and scaled to accommodate different sensors, such as ALOS PALSAR, Landsat, and EnMAP (Brell et al., 2021; Rosenqvist et al., 2007). In this study, we utilized MESMA, an advanced model that only considers only linear mixture mechanisms. However, it is essential to acknowledge that real-world scenarios also involve nonlinearity resulted from the multiple scattering within mixed pixels, which may necessitate more sophisticated models that can accurately represent this complexity in future research. The open structure of the F-SRTMA framework enables the use of other state-of-the-art unmixing algorithms to model both linear and non-linear mixtures, such as regression-based unmixing models (Okujeni et al., 2017; Senf et al., 2020) and spectral-spatial deep learning (Bolyn et al., 2022).

5. Conclusion

Fractional tree functional type (TFT) composition is an important metric that is tightly related to the multi-functionality of temperate mixed forest ecosystems. In this study, we developed an F-SRTMA framework to enhance TFT fraction mapping using time-series Sentinel -1 and -2 data, aiming to advance the characterization of high spatial TFT heterogeneity in temperate mixed forest ecotones. The framework includes four steps: reconstructing standardized SRT features based on time-series Sentinel-1 and -2 imagery (step 1), identifying candidate endmembers using a spatial-guided endmember selection method (step 2), optimizing the endmember space-time variability with FDA (step 3), and estimating the endmember abundances per pixel from a MESMA model (step 4). Our proposed F-SRTMA approach was rigorously evaluated and exhibited higher accuracy (RMSE=0.169, R=0.863) compared to recent advanced STMA (RMSE=0.218, R=0.746) and conventional SMA (RMSE=0.283, R=0.646). Moreover, the inclusion of radar time-series improved generalizability across sites (RMSE=0.262 vs. 0.232, R=0.667 vs. 0.759 for STMA and SRTMA), and the integration of FDA (F-SRTMA) achieved more consistent and significantly higher cross-site accuracy. Our work demonstrates the advantages of integrating spectral and radar time-series signals for improved unmixing modeling, which holds significant theoretical implications. Additionally, our proposed F-SRTMA framework provides an effective way to utilize spectral and radar time series for TFT fractional mapping, offering new avenues for refining the fusion of spectral and radar information.

The framework, built on the GEE platform, facilitates the detection of fractional TFT composition variations across diverse landscapes on an ecoregion level, providing an essential dataset to support subsequent, more complex ecological studies of this system. We contend that our framework could be equally suitable for mapping other important metrics, such as urban and vegetation fractions, and could be scaled for different time-series spectral and radar remote sensing datasets and integrated with various unmixing algorithms.

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All the relevant processes and statistics were coded in JavaScript based on the API of Earth

Engine, and Python 3.9 (Python Software Foundation, https://www.python.org/) and will be shared on GitHub (https://github.com/) upon acceptance.

Credit author statement

J.Wu. and Z.L. designed the study. Z.L. analyzed data. Z.L. drafted the original version of the manuscript. All authors edited and revised the manuscript.

References

Adams, J. B., & Gillespie, A. R. (2006). *Remote Sensing of Landscapes with Spectral Images: A Physical Modeling Approach* (1st ed.). Cambridge University Press. https://doi.org/10.1017/CBO9780511617195

Ahl, D. E., Gower, S. T., Mackay, D. S., Burrows, S. N., Norman, J. M., & Diak, G. R. (2004). Heterogeneity of light use efficiency in a northern Wisconsin forest: Implications for modeling net primary production with remote sensing. *Remote Sensing of Environment*, *93*(1–2), 168–178. https://doi.org/10.1016/j.rse.2004.07.003

Anderegg, W. R. L., Konings, A. G., Trugman, A. T., Yu, K., Bowling, D. R., Gabbitas, R., Karp, D. S., Pacala, S., Sperry, J. S., Sulman, B. N., & Zenes, N. (2018). Hydraulic diversity of forests regulates ecosystem resilience during drought. *Nature*, *561*(7724), Article 7724. https://doi.org/10.1038/s41586-018-0539-7

Arii, M., Yamada, H., Kojima, S., & Ohki, M. (2019). Review of the Comprehensive SAR Approach to Identify Scattering Mechanisms of Radar Backscatter from Vegetated Terrain. *Electronics*, *8*(10), 1098. https://doi.org/10.3390/electronics8101098

Bai, K., He, C., Wan, X., & Jiang, D. (2015). Leaf economics of evergreen and deciduous tree species along an elevational gradient in a subtropical mountain. *AoB PLANTS*, *7*, plv064. https://doi.org/10.1093/aobpla/plv064

Barton, I., Király, G., Czimber, K., Hollaus, M., & Pfeifer, N. (2017). Treefall Gap Mapping Using Sentinel-2 Images. *Forests*, *8*(11), 426. https://doi.org/10.3390/f8110426

Bolyn, C., Lejeune, P., Michez, A., & Latte, N. (2022). Mapping tree species proportions from satellite imagery using spectral–spatial deep learning. *Remote Sensing of Environment*, *280*, 113205. https://doi.org/10.1016/j.rse.2022.113205

Box, E. O., & Fujiwara, K. (Eds.). (2015). *Warm-Temperate Deciduous Forests around the Northern Hemisphere*. Springer International Publishing. https://doi.org/10.1007/978-3-319-01261-2

Brell, M., Guanter, L., Segl, K., Scheffler, D., Bohn, N., Bracher, A., Soppa, M. A., Foerster, S., Storch, T., Bachmann, M., & Chabrillat, S. (2021). The EnMAP Satellite –Data Product Validation Activities. *2021 11th Workshop on Hyperspectral Imaging and Signal Processing: Evolution in Remote Sensing (WHISPERS)*, 1–5. https://doi.org/10.1109/WHISPERS52202.2021.9484000

Bro, R., & Jong, S. D. (1997). A FAST NON-NEGATIVITY-CONSTRAINED LEAST SQUARES ALGORITHM. *Journal of Chemometrics*, *11*, 10.

Carreiras, J. M. B., Quegan, S., Le Toan, T., Ho Tong Minh, D., Saatchi, S. S., Carvalhais, N., Reichstein, M., & Scipal, K. (2017). Coverage of high biomass forests by the ESA BIOMASS mission under defense restrictions. *Remote Sensing of Environment*, *196*, 154–162. https://doi.org/10.1016/j.rse.2017.05.003

Chen, J., Jönsson, Per., Tamura, M., Gu, Z., Matsushita, B., & Eklundh, L. (2004). A simple method for reconstructing a high-quality NDVI time-series data set based on the Savitzky–Golay filter. *Remote Sensing of Environment*, *91*(3), 332–344. https://doi.org/10.1016/j.rse.2004.03.014

Claverie, M., Ju, J., Masek, J. G., Dungan, J. L., Vermote, E. F., Roger, J.-C., Skakun, S. V., & Justice, C. (2018). The Harmonized Landsat and Sentinel-2 surface reflectance data set. *Remote Sensing of Environment*, *219*, 145–161. https://doi.org/10.1016/j.rse.2018.09.002

Comer, M. L. (1999). Morphological operations for color image processing. *Journal of Electronic Imaging*, *8*(3), 279. https://doi.org/10.1117/1.482677

Cook, J. E. (2015). Structural effects on understory attributes in second-growth forests of northern Wisconsin, USA. *Forest Ecology and Management*, *347*, 188–199. https://doi.org/10.1016/j.foreco.2015.03.027

Cooley, S. S., Fisher, J. B., & Goldsmith, G. R. (2022). Convergence in water use efficiency within plant functional types across contrasting climates. *Nature Plants*, *8*(4), Article 4. https://doi.org/10.1038/s41477-022-01131-z

D'Andrimont, R., Yordanov, M., Martinez-Sanchez, L., Eiselt, B., Palmieri, A., Dominici, P., Gallego, J., Reuter, H. I., Joebges, C., Lemoine, G., & Van Der Velde, M. (2020). Harmonised LUCAS in-situ land cover and use database for field surveys from 2006 to 2018 in the European Union. *Scientific Data*, *7*(1). https://doi.org/10.1038/s41597-020-00675-z

Degerickx, J., Roberts, D. A., & Somers, B. (2019). Enhancing the performance of Multiple Endmember Spectral Mixture Analysis (MESMA) for urban land cover mapping using airborne lidar data and band selection. *Remote Sensing of Environment*, *221*, 260–273. https://doi.org/10.1016/j.rse.2018.11.026

Díaz, S., & Cabido, M. (2001). Vive la différence: Plant functional diversity matters to ecosystem processes. *Trends in Ecology & Evolution*, *16*(11), 646–655. https://doi.org/10.1016/S0169-5347(01)02283-2

Dostálová, A., Wagner, W., Milenković, M., & Hollaus, M. (2018). Annual seasonality in Sentinel-1 signal for forest mapping and forest type classification. *International Journal of Remote Sensing*, *39*(21), 7738–7760. https://doi.org/10.1080/01431161.2018.1479788

Echeverría-Londoño, S., Enquist, B. J., Neves, D. M., Violle, C., Boyle, B., Kraft, N. J. B., Maitner, B. S., McGill, B., Peet, R. K., Sandel, B., Smith, S. A., Svenning, J.-C., Wiser,

S. K., & Kerkhoff, A. J. (2018). Plant Functional Diversity and the Biogeography of Biomes in North and South America. *Frontiers in Ecology and Evolution*, *6*, 219. https://doi.org/10.3389/fevo.2018.00219

Englhart, S., Keuck, V., & Siegert, F. (2011). Aboveground biomass retrieval in tropical forests—The potential of combined X- and L-band SAR data use. *Remote Sensing of Environment*, *115*(5), 1260–1271. https://doi.org/10.1016/j.rse.2011.01.008

Espelta, J. M., Cruz-Alonso, V., Alfaro-Sánchez, R., Hampe, A., Messier, C., & Pino, J. (2020). Functional diversity enhances tree growth and reduces herbivory damage in secondary broadleaf forests, but does not influence resilience to drought. *Journal of Applied Ecology*, *57*(12), 2362–2372. https://doi.org/10.1111/1365-2664.13728

Feng, Z., Zheng, X., Li, L., Li, B., Chen, S., Guo, T., Wang, X., Jiang, T., Li, X., & Li, X. (2021). Dynamic Cosine Method for Normalizing Incidence Angle Effect on C-band Radar Backscattering Coefficient for Maize Canopies Based on NDVI. *Remote Sensing*, *13*(15), Article 15. https://doi.org/10.3390/rs13152856

Ferguson, J. E., & Gunn, G. E. (2022). Polarimetric decomposition of microwave-band freshwater ice SAR data: Review, analysis, and future directions. *Remote Sensing of Environment*, *280*, 113176. https://doi.org/10.1016/j.rse.2022.113176

Ferrazzoli, P., & Guerriero, L. (1995). Radar sensitivity to tree geometry and woody volume: A model analysis. *IEEE Transactions on Geoscience and Remote Sensing*, *33*(2), 360–371. https://doi.org/10.1109/tgrs.1995.8746017

Freeman, A., & Durden, S. L. (1998). A three-component scattering model for polarimetric SAR data. *IEEE Transactions on Geoscience and Remote Sensing*, *36*(3), 963–973. https://doi.org/10.1109/36.673687

Gao, L., Wang, X., Johnson, B. A., Tian, Q., Wang, Y., Verrelst, J., Mu, X., & Gu, X. (2020). Remote sensing algorithms for estimation of fractional vegetation cover using pure vegetation index values: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, *159*, 364–377. https://doi.org/10.1016/j.isprsjprs.2019.11.018

Gascoin, S., Grizonnet, M., Bouchet, M., Salgues, G., & Hagolle, O. (2019). Theia Snow collection: High-resolution operational snow cover maps from Sentinel-2 and Landsat-8 data. *Earth System Science Data*, *11*(2), 493–514. https://doi.org/10.5194/essd-11-493-2019

Giordano, S., Mercier, G., & Rudant, J.-P. (2018). Unmixing Polarimetric Radar Images Based on Land Cover Type Identified by Higher Resolution Optical Data Before Target Decomposition: Application to Forest and Bare Soil. *IEEE Transactions on Geoscience and Remote Sensing*, *56*(10), 5850–5862. https://doi.org/10.1109/tgrs.2018.2827258

Gleason, K. E., Bradford, J. B., Bottero, A., D'Amato, A. W., Fraver, S., Palik, B. J., Battaglia, M. A., Iverson, L., Kenefic, L., & Kern, C. C. (2017). Competition amplifies drought stress in forests across broad climatic and compositional gradients. *Ecosphere*, *8*(7), e01849. https://doi.org/10.1002/ecs2.1849

Gómez, C., White, J. C., & Wulder, M. A. (2016). Optical remotely sensed time series data for land cover classification: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, *116*, 55–72. https://doi.org/10.1016/j.isprsjprs.2016.03.008

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Han, X., Xu, Y., Huang, J., & Zang, R. (2022). Species Diversity Regulates Ecological Strategy Spectra of Forest Vegetation Across Different Climatic Zones. *Frontiers in Plant*

Science, *13*. https://www.frontiersin.org/article/10.3389/fpls.2022.807369

Heinz, D. C. & Chein-I-Chang. (2001). Fully constrained least squares linear spectral mixture analysis method for material quantification in hyperspectral imagery. *IEEE Transactions on Geoscience and Remote Sensing*, *39*(3), 529–545. https://doi.org/10.1109/36.911111

Hemmerling, J., Pflugmacher, D., & Hostert, P. (2021). Mapping temperate forest tree species using dense Sentinel-2 time series. *Remote Sensing of Environment*, *267*, 112743. https://doi.org/10.1016/j.rse.2021.112743

Hillebrand, F. L., Bremer, U. F., de Freitas, M. W. D., Costi, J., Mendes Júnior, C. W., Arigony-Neto, J., & Simões, J. C. (2022). Spectral linear mixing model applied to data from passive microwave radiometers for sea ice mapping in the Antarctic Peninsula. *Geocarto International*, *37*(11), 3141–3166. https://doi.org/10.1080/10106049.2020.1856194

Jin, J., Wang, B., & Zhang, L. (2010). A Novel Approach Based on Fisher Discriminant Null Space for Decomposition of Mixed Pixels in Hyperspectral Imagery. *IEEE Geoscience and Remote Sensing Letters*, *7*(4), 699–703. https://doi.org/10.1109/lgrs.2010.2046134

Joshi, N. P., Mitchard, E. T. A., Schumacher, J., Johannsen, V. K., Saatchi, S., & Fensholt, R. (2015). L-Band SAR Backscatter Related to Forest Cover, Height and Aboveground Biomass at Multiple Spatial Scales across Denmark. *Remote Sensing*, *7*(4), Article 4. https://doi.org/10.3390/rs70404442

Jung, M., Arnell, A., de Lamo, X., García-Rangel, S., Lewis, M., Mark, J., Merow, C., Miles, L., Ondo, I., Pironon, S., Ravilious, C., Rivers, M., Schepaschenko, D., Tallowin, O., van Soesbergen, A., Govaerts, R., Boyle, B. L., Enquist, B. J., Feng, X., … Visconti, P. (2021). Areas of global importance for conserving terrestrial biodiversity, carbon and water. *Nature Ecology & Evolution*, *5*(11), 1499–1509. https://doi.org/10.1038/s41559-021-01528-7

Krasnova, A., Kukumägi, M., Mander, Ü., Torga, R., Krasnov, D., Noe, S. M., Ostonen, I., Püttsepp, Ü., Killian, H., Uri, V., Lõhmus, K., Sõber, J., & Soosaar, K. (2019). Carbon exchange in a hemiboreal mixed forest in relation to tree species composition. *Agricultural and Forest Meteorology*, *275*, 11–23. https://doi.org/10.1016/j.agrformet.2019.05.007

Li, X., Liu, Y., Xu, W., Huang, P., & Fu, W. (2019). *Forest Canopy Volume Density Index Inversion Method Using Polarization Decomposition*. 2019 Photonics & Electromagnetics Research Symposium - Fall (PIERS - Fall). https://doi.org/10.1109/piers-fall48861.2019.9021425

Ling, Y., Teng, S., Liu, C., Dash, J., Morris, H., & Pastor-Guzman, J. (2022). Assessing the Accuracy of Forest Phenological Extraction from Sentinel-1 C-Band Backscatter Measurements in Deciduous and Coniferous Forests. *Remote Sensing*, *14*(3), Article 3. https://doi.org/10.3390/rs14030674

Liu, M., Yang, W., Chen, J., & Chen, X. (2017). An Orthogonal Fisher Transformation-Based Unmixing Method Toward Estimating Fractional Vegetation Cover in Semiarid Areas. *IEEE Geoscience and Remote Sensing Letters*, *14*(3), 449–453. https://doi.org/10.1109/lgrs.2017.2648863

Mackay, D. S., Ahl, D. E., Ewers, B. E., Gower, S. T., Burrows, S. N., Samanta, S., & Davis, K. J. (2002). Effects of aggregated classifications of forest composition on estimates of evapotranspiration in a northern Wisconsin forest. *Global Change Biology*, *8*(12), 1253–1265. https://doi.org/10.1046/j.1365-2486.2002.00554.x

Malenovský, Z., Rott, H., Cihlar, J., Schaepman, M. E., García-Santos, G., Fernandes, R., &

Berger, M. (2012). Sentinels for science: Potential of Sentinel-1, -2, and -3 missions for scientific observations of ocean, cryosphere, and land. *Remote Sensing of Environment*, *120*, 91–101. https://doi.org/10.1016/j.rse.2011.09.026

Mamet, S. D., Brown, C. D., Trant, A. J., & Laroque, C. P. (2019). Shifting globalLarixdistributions: Northern expansion and southern retraction as species respond to changing climate. *Journal of Biogeography*, *46*(1), 30–44. https://doi.org/10.1111/jbi.13465

Mei, S., He, M., Wang, Z., & Feng, D. (2010). Spatial Purity Based Endmember Extraction for Spectral Mixture Analysis. *IEEE Transactions on Geoscience and Remote Sensing*, *48*(9), 3434–3445. https://doi.org/10.1109/tgrs.2010.2046671

Mendes, F., Baron, D., Gerold, G., Liesenberg, V., & Erasmi, S. (2019). Optical and SAR Remote Sensing Synergism for Mapping Vegetation Types in the Endangered Cerrado/Amazon Ecotone of Nova Mutum—Mato Grosso. *Remote Sensing*, *11*, 1161. https://doi.org/10.3390/rs11101161

Moore, C. E., Beringer, J., Evans, B., Hutley, L. B., Mchugh, I., & Tapper, N. J. (2016). The contribution of trees and grasses to productivity of an Australian tropical savanna. *Biogeosciences*, *13*(8), 2387–2403. https://doi.org/10.5194/bg-13-2387-2016

Mullissa, A., Vollrath, A., Odongo-Braun, C., Slagter, B., Balling, J., Gou, Y., Gorelick, N., & Reiche, J. (2021). Sentinel-1 SAR Backscatter Analysis Ready Data Preparation in Google Earth Engine. *Remote Sensing*, *13*(10), Article 10. https://doi.org/10.3390/rs13101954

Murphy, B. A., May, J. A., Butterworth, B. J., Andresen, C. G., & Desai, A. R. (2022). Unraveling Forest Complexity: Resource Use Efficiency, Disturbance, and the Structure-Function Relationship. *Journal of Geophysical Research: Biogeosciences*, *127*(6), e2021JG006748. https://doi.org/10.1029/2021JG006748

NatureServe. (2018). *International Ecological Classification Standard: Terrestrial Ecological Classifications. NatureServe Central Databases. Arlington, VA. U.S.A. Data current as of 28 August 2018* [dataset].

Neves, D. M., Kerkhoff, A. J., Echeverría-Londoño, S., Merow, C., Morueta-Holme, N., Peet, R. K., Sandel, B., Svenning, J.-C., Wiser, S. K., & Enquist, B. J. (2021). The adaptive challenge of extreme conditions shapes evolutionary diversity of plant assemblages at continental scales. *Proceedings of the National Academy of Sciences*, *118*(37), e2021132118. https://doi.org/10.1073/pnas.2021132118

Nill, L., Grünberg, I., & Ullmann, T. (2022). Arctic shrub expansion revealed by Landsat-derived multitemporal vegetation cover fractions in the Western Canadian Arctic. *Remote Sensing of Environment*, *281*, 113228. https://doi.org/10.1016/j.rse.2022.113228

Okada, T., & Tomita, S. (1985). An optimal orthonormal system for discriminant analysis. *Pattern Recognition*, *18*(2), 139–144. https://doi.org/10.1016/0031-3203(85)90037-8

Okujeni, A., Jänicke, C., Cooper, S., Frantz, D., Hostert, P., Clark, M., Segl, K., & van der Linden, S. (2021). Multi-season unmixing of vegetation class fractions across diverse Californian ecoregions using simulated spaceborne imaging spectroscopy data. *Remote Sensing of Environment*, *264*, 112558. https://doi.org/10.1016/j.rse.2021.112558

Okujeni, A., van der Linden, S., Suess, S., & Hostert, P. (2017). Ensemble Learning From Synthetically Mixed Training Data for Quantifying Urban Land Cover With Support Vector Regression. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *10*(4), 1640–1650. https://doi.org/10.1109/JSTARS.2016.2634859

Otsu, N. (1979). A Threshold Selection Method from Gray-Level Histograms. *IEEE Transactions on Systems, Man, and Cybernetics*, *9*(1), 62–66. https://doi.org/10.1109/TSMC.1979.4310076

Ouyang, L., Wu, C., Li, J., Liu, Y., Wang, M., Han, J., Song, C., Yu, Q., & Haase, D. (2022). Mapping Impervious Surface Using Phenology-Integrated and Fisher Transformed Linear Spectral Mixture Analysis. *Remote. Sens.* https://doi.org/10.3390/rs14071673

Parida, B. R., & Mandal, S. P. (2020). Polarimetric decomposition methods for LULC mapping using ALOS L-band PolSAR data in Western parts of Mizoram, Northeast India. *SN Applied Sciences*, *2*(6). https://doi.org/10.1007/s42452-020-2866-1

Plaza, A., Martinez, P., Perez, R., & Plaza, J. (2002). Spatial/spectral endmember extraction by multidimensional morphological operations. *IEEE Transactions on Geoscience and Remote Sensing*, *40*(9), 2025–2041. https://doi.org/10.1109/tgrs.2002.802494

Potapov, P., Li, X., Hernandez-Serna, A., Tyukavina, A., Hansen, M. C., Kommareddy, A., Pickens, A., Turubanova, S., Tang, H., Silva, C. E., Armston, J., Dubayah, R., Blair, J. B., & Hofton, M. (2021). Mapping global forest canopy height through integration of GEDI and Landsat data. *Remote Sensing of Environment*, *253*, 112165. https://doi.org/10.1016/j.rse.2020.112165

Poulter, B., Macbean, N., Hartley, A., Khlystova, I., Arino, O., Betts, R., Bontemps, S., Boettcher, M., Brockmann, C., Defourny, P., Hagemann, S., Herold, M., Kirches, G., Lamarche, C., Lederer, D., Ottlé, C., Peters, M., & Peylin, P. (2015). Plant functional type classification for earth system models: Results from the European Space Agency's Land Cover Climate Change Initiative. *Geoscientific Model Development*, *8*(7), 2315–2328. https://doi.org/10.5194/gmd-8-2315-2015

Powell, R. L., Roberts, D. A., Dennison, P. E., & Hess, L. L. (2007). Sub-pixel mapping of urban land cover using multiple endmember spectral mixture analysis: Manaus, Brazil. *Remote Sensing of Environment*, *106*(2), 253–267. https://doi.org/10.1016/j.rse.2006.09.005

Quintano, C., Fernández-Manso, A., Shimabukuro, Y. E., & Pereira, G. (2012). Spectral unmixing. *International Journal of Remote Sensing*, *33*(17), 5307–5340. https://doi.org/10.1080/01431161.2012.661095

Reiche, J., Hamunyela, E., Verbesselt, J., Hoekman, D., & Herold, M. (2018). Improving near-real time deforestation monitoring in tropical dry forests by combining dense Sentinel-1 time series with Landsat and ALOS-2 PALSAR-2. *Remote Sensing of Environment*, *204*, 147–161. https://doi.org/10.1016/j.rse.2017.10.034

Roberts, D. A., Gardner, M., Church, R., Ustin, S., Scheer, G., & Green, R. O. (1998). Mapping Chaparral in the Santa Monica Mountains Using Multiple Endmember Spectral Mixture Models. *Remote Sensing of Environment*, *65*(3), 267–279. https://doi.org/10.1016/S0034-4257(98)00037-6

Roger, R. E. (1996). Principal Components transform with simple, automatic noise adjustment. *International Journal of Remote Sensing*, *17*(14), 2719–2727. https://doi.org/10.1080/01431169608949102

Rosenqvist, A., Shimada, M., Ito, N., & Watanabe, M. (2007). ALOS PALSAR: A Pathfinder Mission for Global-Scale Monitoring of the Environment. *IEEE Transactions on Geoscience and Remote Sensing*, *45*(11), 3307–3316. https://doi.org/10.1109/TGRS.2007.901027

Roth, K. L., Dennison, P. E., & Roberts, D. A. (2012). Comparing endmember selection techniques for accurate mapping of plant species and land cover using imaging spectrometer data. *Remote Sensing of Environment*, 14.

Schubert, A., Miranda, N., Geudtner, D., & Small, D. (2017). Sentinel-1A/B Combined Product Geolocation Accuracy. *Remote Sensing*, *9*(6), Article 6. https://doi.org/10.3390/rs9060607

Schug, F., Frantz, D., Okujeni, A., van der Linden, S., & Hostert, P. (2020). Mapping urban-rural gradients of settlements and vegetation at national scale using Sentinel-2 spectral-temporal metrics and regression-based unmixing with synthetic training data. *Remote Sensing of Environment*, *246*, 111810. https://doi.org/10.1016/j.rse.2020.111810

Sedehi, M., Carbone, A., Imbembo, E., Heliere, F., Rommen, B., Fehringer, M., Scipal, K., Leanza, A., Simon, T., & Willemsen, P. (2021). Biomass—A fully polarimetric P-band SAR ESA mission. *EUSAR 2021; 13th European Conference on Synthetic Aperture Radar*, 1–5.

Senf, C., Laštovička, J., Okujeni, A., Heurich, M., & van der Linden, S. (2020). A generalized regression-based unmixing model for mapping forest cover fractions throughout three decades of Landsat data. *Remote Sensing of Environment*, *240*, 111691. https://doi.org/10.1016/j.rse.2020.111691

Shi, C., & Wang, L. (2014). Incorporating spatial information in spectral unmixing: A review. *Remote Sensing of Environment*, *149*, 70–87. https://doi.org/10.1016/j.rse.2014.03.034

Singh, G., Malik, R., Mohanty, S., Rathore, V. S., Yamada, K., Umemura, M., & Yamaguchi, Y. (2019). Seven-Component Scattering Power Decomposition of POLSAR Coherency Matrix. *IEEE Transactions on Geoscience and Remote Sensing*, *57*(11), 8371–8382. https://doi.org/10.1109/tgrs.2019.2920762

Smith, N. G., & Keenan, T. F. (2020). Mechanisms underlying leaf photosynthetic acclimation to warming and elevated CO 2 as inferred from least-cost optimality theory. *Global Change Biology*, *26*(9), 5202–5216. https://doi.org/10.1111/gcb.15212

Somers, B., Asner, G. P., Tits, L., & Coppin, P. (2011). Endmember variability in Spectral Mixture Analysis: A review. *Remote Sensing of Environment*, *115*(7), 1603–1616. https://doi.org/10.1016/j.rse.2011.03.003

Sonnier, G., Johnson, S. E., & Waller, D. M. (2020). Fragmentation reduces the importance of niche-based factors relative to dispersal traits in structuring temperate forest understories. *Journal of Vegetation Science*, *31*(1), 75–83. https://doi.org/10.1111/jvs.12824

Sousa, D., & Davis, F. W. (2020). Scalable mapping and monitoring of Mediterranean-climate oak landscapes with temporal mixture models. *Remote Sensing of Environment*, *247*, 111937. https://doi.org/10.1016/j.rse.2020.111937

Swenson, N. G., Enquist, B. J., Pither, J., Kerkhoff, A. J., Boyle, B., Weiser, M. D., Elser, J. J., Fagan, W. F., Forero-Montaña, J., Fyllas, N., Kraft, N. J. B., Lake, J. K., Moles, A. T., Patiño, S., Phillips, O. L., Price, C. A., Reich, P. B., Quesada, C. A., Stegen, J. C., … Nolting, K. M. (2012). The biogeography and filtering of woody plant functional diversity in North and South America: Functional trait biogeography. *Global Ecology and Biogeography*, *21*(8), 798–808. https://doi.org/10.1111/j.1466-8238.2011.00727.x

Tanase, M. A., Villard, L., Pitar, D., Apostol, B., Petrila, M., Chivulescu, S., Leca, S., Borlaf-Mena, I., Pascu, I.-S., Dobre, A.-C., Pitar, D., Guiman, G., Lorent, A., Anghelus, C., Ciceu, A., Nedea, G., Stanculeanu, R., Popescu, F., Aponte, C., & Badea, O. (2019). Synthetic aperture radar sensitivity to forest changes: A simulations-based study for the Romanian forests. *Science of The Total Environment*, *689*, 1104–1114. https://doi.org/10.1016/j.scitotenv.2019.06.494

Tian, D., & Wang, L. (2022). Subpixel Melt Index in the Antarctic Peninsula Using Spatially Constrained Linear Unmixing From Time Series Satellite Passive Microwave Images.

IEEE Transactions on Geoscience and Remote Sensing, *60*, 1–9. https://doi.org/10.1109/tgrs.2020.3043330

Ustin, S. L., & Gamon, J. A. (2010). Remote sensing of plant functional types. *New Phytologist*, *186*(4), 795–816. https://doi.org/10.1111/j.1469-8137.2010.03284.x

Van Cleemput, E., Helsen, K., Feilhauer, H., Honnay, O., & Somers, B. (2021). Spectrally defined plant functional types adequately capture multidimensional trait variation in herbaceous communities. *Ecological Indicators*, *120*, 106970. https://doi.org/10.1016/j.ecolind.2020.106970

Van Der Plas, F., Manning, P., Allan, E., Scherer-Lorenzen, M., Verheyen, K., Wirth, C., Zavala, M. A., Hector, A., Ampoorter, E., Baeten, L., Barbaro, L., Bauhus, J., Benavides, R., Benneter, A., Berthold, F., Bonal, D., Bouriaud, O., Bruelheide, H., Bussotti, F., … Fischer, M. (2016). Jack-of-all-trades effects drive biodiversity–ecosystem multifunctionality relationships in European forests. *Nature Communications*, *7*(1), 11109. https://doi.org/10.1038/ncomms11109

van Geffen, F., Heim, B., Brieger, F., Geng, R., Shevtsova, I. A., Schulte, L., Stuenzi, S. M., Bernhardt, N., Troeva, E. I., Pestryakova, L. A., Zakharov, E. S., Pflug, B., Herzschuh, U., & Kruse, S. (2022). SiDroForest: A comprehensive forest inventory of Siberian boreal forest investigations including drone-based point clouds, individually labeled trees, synthetically generated tree crowns, and Sentinel-2 labeled image patches. *Earth System Science Data*, *14*(11), 4967–4994. https://doi.org/10.5194/essd-14-4967-2022

Verhegghen, A., Kuzelova, K., Syrris, V., Eva, H., & Achard, F. (2022). Mapping Canopy Cover in African Dry Forests from the Combined Use of Sentinel-1 and Sentinel-2 Data: Application to Tanzania for the Year 2018. *Remote Sensing*, *14*(6), Article 6. https://doi.org/10.3390/rs14061522

Vollrath, A., Mullissa, A., & Reiche, J. (2020). Angular-Based Radiometric Slope Correction for Sentinel-1 on Google Earth Engine. *Remote Sensing*, *12*(11), Article 11. https://doi.org/10.3390/rs12111867

Waller, D., Amatangelo, K., Johnson, S., & Rogers, D. (2013). Wisconsin Vegetation Database – plant community survey and resurvey data from the Wisconsin Plant Ecology Laboratory. *Biodiversity & Ecology*, *4*, 255–264. https://doi.org/10.7809/b-e.00082

Wang, J., Song, G., Liddell, M., Morellato, P., Lee, C. K. F., Yang, D., Alberton, B., Detto, M., Ma, X., Zhao, Y., Yeung, H. C. H., Zhang, H., Ng, M., Nelson, B. W., Huete, A., & Wu, J. (2023). An ecologically-constrained deep learning model for tropical leaf phenology monitoring using PlanetScope satellites. *Remote Sensing of Environment*, *286*, 113429. https://doi.org/10.1016/j.rse.2022.113429

Wang, Q., Ding, X., Tong, X., & Atkinson, P. M. (2021). Spatio-temporal spectral unmixing of time-series images. *Remote Sensing of Environment*, *259*, 112407. https://doi.org/10.1016/j.rse.2021.112407

Waser, L. T., Rüetschi, M., Psomas, A., Small, D., & Rehush, N. (2021). Mapping dominant leaf type based on combined Sentinel-1/-2 data – Challenges for mountainous countries. *ISPRS Journal of Photogrammetry and Remote Sensing*, *180*, 209–226. https://doi.org/10.1016/j.isprsjprs.2021.08.017

Weinstein, B. G., Marconi, S., Bohlman, S., Zare, A., & White, E. (2019). Individual Tree-Crown Detection in RGB Imagery Using Semi-Supervised Deep Learning Neural Networks. *Remote Sensing*, *11*(11), 1309. https://doi.org/10.3390/rs11111309

Wiegmann, S. M., & Waller, D. M. (2006). Fifty years of change in northern upland forest understories: Identity and traits of "winner" and "loser" plant species. *Biological Conservation*, *129*(1), 109–123. https://doi.org/10.1016/j.biocon.2005.10.027

Wu, J., Kobayashi, H., Stark, S. C., Meng, R., Guan, K., Tran, N. N., Gao, S., Yang, W., Restrepo-Coupe, N., Miura, T., Oliviera, R. C., Rogers, A., Dye, D. G., Nelson, B. W., Serbin, S. P., Huete, A. R., & Saleska, S. R. (2018). Biological processes dominate seasonality of remotely sensed canopy greenness in an Amazon evergreen forest. *The New Phytologist*, *217*(4), 1507–1520. https://doi.org/10.1111/nph.14939

Wu, S., Wang, J., Yan, Z., Song, G., Chen, Y., Ma, Q., Deng, M., Wu, Y., Zhao, Y., Guo, Z., Yuan, Z., Dai, G., Xu, X., Yang, X., Su, Y., Liu, L., & Wu, J. (2021). Monitoring tree-crown scale autumn leaf phenology in a temperate forest with an integration of PlanetScope and drone remote sensing observations. *ISPRS Journal of Photogrammetry and Remote Sensing*, *171*, 36–48. https://doi.org/10.1016/j.isprsjprs.2020.10.017

Xu, F., Cao, X., Chen, X., & Somers, B. (2019). Mapping impervious surface fractions using automated Fisher transformed unmixing. *Remote Sensing of Environment*, *232*, 111311. https://doi.org/10.1016/j.rse.2019.111311

Yang, X., Tang, J., & Mustard, J. F. (2014). Beyond leaf color: Comparing camera-based phenological metrics with leaf biochemical, biophysical, and spectral properties throughout the growing season of a temperate deciduous forest. *Journal of Geophysical Research: Biogeosciences*, *119*(3), 181–191. https://doi.org/10.1002/2013JG002460

Yang, Y., Wu, T., Zeng, Y., & Wang, S. (2021). An Adaptive-Parameter Pixel Unmixing Method for Mapping Evergreen Forest Fractions Based on Time-Series NDVI: A Case Study of Southern China. *Remote Sensing*, *13*(22), 4678. https://doi.org/10.3390/rs13224678

Yin, G., Li, A., Wu, S., Fan, W., Zeng, Y., Yan, K., Xu, B., Li, J., & Liu, Q. (2018). PLC: A simple and semi-physical topographic correction method for vegetation canopies based on path length correction. *Remote Sensing of Environment*, *215*, 184–198.

https://doi.org/10.1016/j.rse.2018.06.009

Yommy, A. S., Liu, R., & Wu, A. S. (2015). *SAR Image Despeckling Using Refined Lee Filter*. 2015 7th International Conference on Intelligent Human-Machine Systems and Cybernetics. https://doi.org/10.1109/ihmsc.2015.236

Zanaga, Daniele, Van De Kerchove, Ruben, De Keersmaecker, Wanda, Souverijns, Niels, Brockmann, Carsten, Quast, Ralf, Wevers, Jan, Grosu, Alex, Paccini, Audrey, Vergnaud, Sylvain, Cartus, Oliver, Santoro, Maurizio, Fritz, Steffen, Georgieva, Ivelina, Lesiv, Myroslava, Carter, Sarah, Herold, Martin, Li, Linlin, Tsendbazar, Nandin-Erdene, … Arino, Olivier. (2021). *ESA WorldCover 10 m 2020 v100* (Version v100) [dataset]. Zenodo. https://doi.org/10.5281/ZENODO.5571936

Zhang, C., Ma, L., Chen, J., Rao, Y., Zhou, Y., & Chen, X. (2019). Assessing the impact of endmember variability on linear Spectral Mixture Analysis (LSMA): A theoretical and simulation analysis. *Remote Sensing of Environment*, *235*, 111471. https://doi.org/10.1016/j.rse.2019.111471

Zhao, F., Sun, R., Zhong, L., Meng, R., Huang, C., Zeng, X., Wang, M., Li, Y., & Wang, Z. (2022). Monthly mapping of forest harvesting using dense time series Sentinel-1 SAR imagery and deep learning. *Remote Sensing of Environment*, *269*, 112822. https://doi.org/10.1016/j.rse.2021.112822

Zhao, Y., Lee, C. K. F., Wang, Z., Wang, J., Gu, Y., Xie, J., Law, Y. K., Song, G., Bonebrake, T. C., Yang, X., Nelson, B. W., & Wu, J. (2022). Evaluating fine-scale phenology from PlanetScope satellites with ground observations across temperate forests in eastern North America. *Remote Sensing of Environment*, *283*, 113310. https://doi.org/10.1016/j.rse.2022.113310

Zhong, Z., Li, J., Luo, Z., & Chapman, M. (2018). Spectral–Spatial Residual Network for

Hyperspectral Image Classification: A 3-D Deep Learning Framework. *IEEE Transactions on Geoscience and Remote Sensing*, *56*(2), 847–858. https://doi.org/10.1109/tgrs.2017.2755542

Zhuo, R., Fang, Y., Xu, L., Chen, Y., Wang, Y., & Peng, J. (2022). A novel spectral-temporal Bayesian unmixing algorithm with spatial prior for Sentinel-2 time series. *Remote Sensing Letters*, *13*(5), 522–532. https://doi.org/10.1080/2150704x.2022.2044087