

Article

Subpixel Mapping of Flammable Tree Species in Yajiang County Based on Sentinel-2 Time-Series Data and a Spectral Mixing–Unmixing Strategy

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Highlights

What are the main findings?

- A Sentinel-2 time-series spectral mixing–unmixing framework was developed for subpixel mapping of flammable tree species in complex mountainous forests.
- The framework achieved reliable abundance estimation ($R^2 = 0.821$) and high NFI-based mapping accuracy, effectively revealing the spatial distribution and composition of flammable tree species.

What are the implications of the main findings?

- The proposed approach provides useful support for forest fuel assessment, fire risk monitoring, and precision forest management.
- Continuous abundance estimation improves the representation of within-pixel species composition compared with conventional hard classification.

Abstract

The spatial distribution of flammable tree species directly influences forest fuel structure and fire risk patterns. However, mixed pixels limit the ability of conventional classification methods to characterize continuous within-pixel variation in species composition, thereby constraining fine-scale forest mapping. To address this issue, this study developed a subpixel mapping framework for flammable tree species in Yajiang County, Sichuan Province, by integrating Sentinel-2 time-series data with a spectral mixing–unmixing strategy. Using 2019 Sentinel-2 time-series data and National Forest Inventory (NFI) data, temporal mixed samples with known abundance fractions were generated using a linear spectral mixing model. An XGBoost-based collaborative multi-regression framework was then applied to estimate the proportions of different tree-species endmembers within complex forest pixels. Quantitative evaluation using synthetic mixed samples showed that the model achieved stable unmixing performance across different random mixing scenarios. The best performance was obtained under the Mixed 2 scenario with a sample size of 250 K, reaching an R^2 of 0.821. The resulting maps revealed continuous spatial variation in the abundance and composition of flammable tree species. Mountain pine was the most widespread and dominant species, followed by spruce and mountain oak, whereas birch and fir mainly exhibited localized patchy distributions. An additional NFI-based categorical evaluation assessed the consistency of the final maps with real forest inventory records. The identification accuracies were 93.95% for pure stands and 91.22% for mixed stands, while the species



Academic Editor: Krzysztof Stereńczak

Received: 26 April 2026

Revised: 4 June 2026

Accepted: 10 June 2026

Published: 12 June 2026

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classification accuracies were 87.28% for pure stands and 84.41% for dominant species in mixed stands. The proposed framework provides useful spatial information for regional forest fuel assessment and fire risk management.

Keywords: flammable tree species; Sentinel-2 time-series; spectral mixing–unmixing; subpixel mapping; forest fire management

1. Introduction

As an important component of forest fuels, the species composition, spatial distribution, and aggregation patterns of flammable tree species strongly influence stand combustibility, fire hazard levels, and wildfire spread potential [1–4]. Accurate identification of flammable tree species and characterization of their spatial distribution are therefore fundamental to forest fire risk assessment and the maintenance of regional ecological security [5]. Traditional field-based survey methods generally suffer from high labor demands, long survey cycles, and limited spatial coverage [6], making them inadequate for the rapid identification and dynamic monitoring of flammable tree species across large areas with complex terrain [7]. In contrast, remote sensing, with its advantages of large-area synoptic observation, high timeliness, and continuous spatial coverage, has gradually emerged as an effective approach for identifying flammable tree species at the regional scale [8,9].

Satellite-image-based tree species mapping has become an important focus in forest resource monitoring and vegetation classification research [10,11]. Previous studies have shown that multispectral remote sensing data, particularly Sentinel-2 imagery, hold substantial potential for tree species identification [12,13]. With a spatial resolution of 10–20 m, Sentinel-2 data provide a good balance between regional coverage and land-cover discrimination accuracy [14]. However, differences among tree species are reflected not only in static spectral characteristics but also in phenological changes associated with budburst, leaf expansion, vigorous growth, and senescence during the growing season [15,16]. For example, Immitzer et al. [17] demonstrated that multi-temporal Sentinel-2 observations acquired during key forest growth periods can effectively improve the discrimination accuracy of different tree species. Compared with single-date approaches, time-series methods can continuously characterize vegetation growth dynamics over time and, by integrating information from different phenological stages, more effectively capture subtle interspecific differences [18]. As highlighted by Hemmerling et al. [14] and Yang et al. [19], the seasonal information contained in time-series data is a key factor in improving tree species mapping accuracy in complex forest environments, although the need for dense data inputs has constrained its broader application. Although the high revisit frequency of Sentinel-2 ensures the acquisition of more usable images within a given time period, challenges such as image processing costs and the absence of observations during critical phenological windows still substantially increase the difficulty of constructing and applying time-series datasets at the regional scale [20].

Despite the substantial progress made in forest mapping in recent years—for example, Zhang et al. [21] improved forest cover information retrieval through a global forest type product constructed from a large number of pure pixels—such approaches essentially assume that each target pixel is compositionally homogeneous and assign a single class label based on the spectral dominance of the prevailing type [22]. For complex land surface objects, however, individual pixels often contain multiple components simultaneously, including different tree species, shrubs and grasses, bare ground, and shadow, making mixed pixels a common phenomenon [23]. This subpixel-level compositional heterogeneity

alters the actual spectral expression of target tree species in remote sensing imagery, causing their spectral signatures to be diluted and interfered with by surrounding background information [24].

Previous studies have attempted to characterize the coexistence of multiple components within forest stands by constructing mixed samples [7], for example, some studies have developed models to predict within-forest compositional members based on the basal area proportions of different tree species measured in field plots [25]. Although such approaches partially overcome the limitations of single-label classification, spectral responses in remote sensing imagery are more strongly determined by canopy properties; therefore, sample relationships established from ground-based structural proportions may still deviate from the actual mixing mechanisms observed in remotely sensed data [26]. In addition, these methods usually rely on large volumes of field-measured data, which constrains their transferability to unobserved regions [9,19]. Spectral mixing–unmixing provides an alternative framework for subpixel mapping in complex forest environments [27]. This approach treats a mixed pixel as the result of linear combinations of endmember spectra in different proportions. Using a limited number of representative endmember spectra, a large set of synthetic samples with known component fractions can be generated according to predefined mixing rules, and regression relationships between spectral features and component abundances can then be established to estimate the proportions of individual constituents within mixed pixels [28,29]. This framework has been widely validated in land-cover fraction mapping [27]. For instance, Schug et al. [30] developed regression models based on synthetic mixed samples to achieve large-scale land-cover fraction mapping.

However, traditional linear-regression-based unmixing still has clear limitations in practice. When input features are expanded to include multi-temporal observations and multiple indices, conventional linear regression models have limited ability to capture the complex relationships embedded in high-dimensional feature space [24]. Machine learning regression models have therefore attracted increasing attention because of their strong feature-learning capability and flexibility in modeling complex relationships. Methods such as random forests and extreme gradient boosting have demonstrated robust performance in remote-sensing regression tasks, including vegetation parameter retrieval [19]. Unlike conventional linear models, these approaches are not restricted to simple linear assumptions and can capture more complex nonlinear responses between input features and target variables [31]. Therefore, integrating linear spectral mixing concepts with machine learning regression models makes it possible to fit the complex relationships between endmember fractions and high-dimensional spectral–temporal features, thereby improving the accuracy and stability of abundance estimation for mixed pixels [24]. Nevertheless, subpixel mapping in forests remains challenging. Spectral differences among tree species are often subtle, whereas within-class spectral variability can be much greater due to phenological variation, topographic effects, and shadow interference, making the mixing relationships among tree species and background components considerably more complex [32]. Consequently, developing an unmixing framework that simultaneously ensures physical interpretability and strong predictive performance in complex forest environments remains an important challenge in forest subpixel mapping research.

Against this background, this study selected Yajiang County, Sichuan Province, as the study area and developed a subpixel mapping framework integrating Sentinel-2 time-series data with a spectral mixing–unmixing strategy. The primary objective was to estimate the within-pixel abundance fractions of flammable tree species. Based on these abundance estimates, dominant-species maps were further generated to characterize the spatial distribution patterns of flammable tree species and support regional forest fuel assessment.

2. Study Area

The study area is Yajiang County, Ganzi Tibetan Autonomous Prefecture, Sichuan Province, located at the junction of the southeastern Qinghai–Tibet Plateau and the Hengduan Mountains, in the middle reaches of the Yalong River (Figure 1). Covering approximately 7569.53 km², the region is characterized by alpine canyon landforms, strong topographic relief, and elevations exceeding 5000 m. It has a plateau continental monsoon climate. Driven by topographic gradients and climatic variation, tree species in the area show clear differences in growth rhythm, canopy structure, and spectral response. Yajiang is an important forest ecological unit in the alpine canyon region of western Sichuan, with forest cover exceeding 56.4%. Tree species are diverse, and major species include spruce (*Picea*), mountain pine (*Pinus densata*), mountain oak (*Quercus*), birch (*Betula*) and fir (*Abies*). Forest fuel composition is highly heterogeneous because species differ in leaf morphology, moisture characteristics, and volatile compounds. In addition, steep slopes, deep valleys, and strong wind disturbances increase the spread risk of forest fires. Therefore, Yajiang provides a representative study area for subpixel mapping of flammable tree species and offers a useful reference for fine-scale forest fuel mapping and fire risk monitoring in alpine canyon regions.

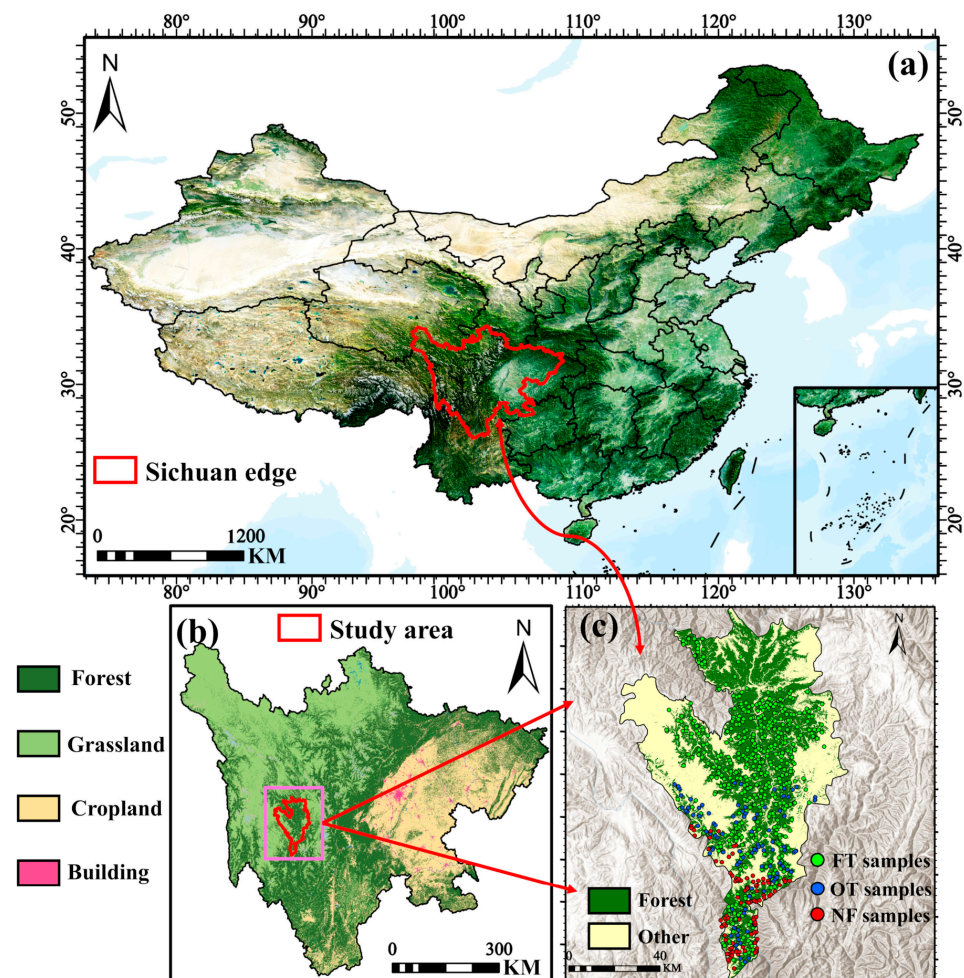


Figure 1. Overview of the study area. (a) Location of Sichuan Province within China; (b) location of the study area within Sichuan Province and its land-cover types; and (c) forest cover in the study area. FT: flammable tree; OT: other tree; NF: non-forest.

3. Data and Methods

3.1. Data Collection and Processing

3.1.1. Sentinel-2 Data Acquisition and Processing

Sentinel-2 raw data acquisition and preprocessing were conducted on the Google Earth Engine (GEE) platform using Level-2A surface reflectance products for the period from 1 January to 31 December 2019. Observations with cloud cover less than 80% were retained, resulting in a total of 426 valid images. To reduce the effects of clouds and cloud shadows, preprocessing involved QA-band-based masking to remove low-quality observations. Considering that tree species identification is sensitive to visible, near-infrared, red-edge, and shortwave infrared information, nine bands—B2, B3, B4, B5, B6, B7, B8, B11, and B12—were retained as input variables for subsequent analysis. Among these, the 20 m bands were resampled to 10 m using bilinear interpolation to ensure spatial consistency.

A range of vegetation indices reflecting vegetation growth status, canopy structure, and red-edge variation were further calculated. The Jeffries–Matusita (J–M) distance [33] was then used to evaluate the spectral separability of different features (detailed separability results are provided in Supplementary Table S1). Ultimately, the Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), and Red-Edge Inflection Point Index (REIP) were selected as important auxiliary variables for subsequent analysis. Detailed information and formulas for these vegetation indices are provided in Table 1.

Table 1. Sources and Formulas of Selected Vegetation Indices.

Spectral Indices	Formula
NDVI [34]	$(B8 - B4)/(B8 + B4)$
SAVI [35]	$(1 + 0.2) \times \text{float}(B8 - B4)/(B8 + B4 + 0.2)$
REIP [36]	$705 + 35 \times ((B4 + B7)/2 - (B5/B6) - B5)$

In the temporal dimension, a 10-day compositing strategy was adopted to reconstruct the original irregular observation sequence. The full year was divided into 36 time steps, each corresponding to a 10-day temporal window. Within each window, multiple quality-controlled images were composited using the median value to reduce the influence of residual cloud contamination and local outliers. After 10-day compositing, an initial multiband time-series dataset with a fixed temporal resolution of 10 days was generated for the study area.

To address missing observations and invalid pixels in the initial time series, temporal gap filling was performed locally. For each pixel and each band, the one-dimensional reflectance sequence along the temporal dimension was reconstructed using linear interpolation to fill missing observations. Specifically, the reflectance value at each missing time step was estimated based on the nearest valid observations before and after the gap, assuming a linear change between adjacent dates. Subsequently, S–G filtering was applied to smooth the time series of each pixel and remove high-frequency noise. After gap filling and smoothing reconstruction, an evenly spaced dense time-series dataset covering the entire year of 2019 was generated, with a fixed temporal interval of 10 days. This dataset consisted of 36 time steps and 12 bands, yielding 432-dimensional temporal reflectance features for each pixel.

3.1.2. Reference Data Collection and Processing

The 2019 National Forest Inventory (NFI) data were used to construct the reference sample set. These vector polygon data provide continuous delineation of forest resources across the study area and include attributes such as forest origin, forest type, dominant species, stand age, canopy closure, and health status. Before use, the NFI data underwent

systematic quality control. Polygons with unclear species composition, missing key attributes, ambiguous forest classes, excessively small areas, fragmented shapes, or highly complex boundaries were removed to reduce boundary mixing and spatial mismatch.

Target species were selected by considering their spatial distribution, contribution to stock, and representativeness in the local forest fuel structure. Based on NFI statistics and the potential flammability of different species, five flammable tree species—mountain pine, spruce, mountain oak, fir, and birch—were chosen for subsequent mapping. These species are widely distributed and ecologically representative in the study area, covering both coniferous and broadleaf forest types.

Samples were extracted only from polygons with clear species composition, good stand continuity, and relatively low internal heterogeneity. A sufficient buffer from polygon boundaries was maintained to minimize edge effects, and candidate samples were further checked using high-resolution Google Earth imagery to exclude pixels affected by understory exposure, roads, or terrain shadow. For each of the five target species, 100 pure pixels were selected; 100 pure pixels were also labeled as other tree species. In addition, 50 shadow pixels and 50 non-forest pixels were selected as background endmembers. This produced a seven-endmember sample system, including five target species, one other-species class, and one background class. The “other tree species” class was treated as an operational composite endmember representing non-target forest components. Because this category may include species with different canopy structures and phenological characteristics, its internal spectral variability should be considered when interpreting the abundance estimates.

The endmember library was intentionally constructed using a limited number of carefully screened samples to evaluate the feasibility of the proposed framework under constrained reference-data conditions. Although a more stratified endmember design could further improve model stability, it would require substantially more reference data and manual screening effort.

3.2. Methods

3.2.1. Construction of the Mixed-Sample Database

In this study, large-scale temporal mixed samples were generated from the pure endmember sample library. The mixing process was based on the linear spectral mixing model (LSMM), which can be expressed as follows:

$$R_{t,\lambda} = \sum_{i=1}^n f_i E_{i,t,\lambda} \quad (1)$$

where $R_{t,\lambda}$ denotes the reflectance of a mixed sample at time step t and band λ , $E_{i,t,\lambda}$ denotes the reflectance of the i -th endmember at the corresponding time step and band, f_i represents the abundance fraction of that endmember within the mixed pixel, and n is the number of endmember classes involved in the mixing process. The mixing operation was not performed for a single time step or band independently; rather, it was implemented synchronously across the full temporal dimension, such that the annual time-series curves of each endmember were combined by weighted summation across all time steps and bands according to their assigned proportions.

During mixed-sample generation, the pure-pixel sample library constructed above was used as the basis. A subset of endmember classes was first randomly selected from the endmember library, and then specific endmember spectral curves were randomly drawn from the corresponding pure-pixel samples for mixing. After endmember sampling, abundance values were randomly assigned to each selected endmember, and the resulting

abundance vector was constrained such that all endmember fractions satisfied the non-negativity condition:

$$f_i \geq 0, \quad i = 1, 2, \dots, n \quad (2)$$

Meanwhile, the randomly generated raw abundance vector was normalized to satisfy the sum-to-one constraint:

$$\sum_{i=1}^n f_i = 1 \quad (3)$$

The normalized abundance coefficients were then directly used to linearly weight the endmember time-series curves, producing the final mixed samples. This random mixing strategy was designed to cover a broad range of potential abundance combinations and to provide explicit abundance labels for model training. However, it represents an idealized mixing space and does not explicitly account for ecological constraints such as species co-occurrence probabilities, habitat-dependent coexistence patterns, or topographic conditions.

This strategy was designed to broaden the coverage of the abundance space and generate mixed samples with explicit fraction labels. However, the resulting synthetic mixtures represent an idealized mixing space because ecological constraints such as species co-occurrence probabilities, habitat-dependent coexistence patterns, and topographic conditions were not explicitly incorporated. Consequently, some simulated combinations may occur infrequently in real forest environments. Each generated sample contained two types of information: high-dimensional input features formed by the combined endmember time-series curves and the corresponding endmember abundance vector used as the supervisory label for subsequent regression modeling.

A progressive expansion strategy was adopted to determine sample size. To examine the effect of training sample quantity on model performance, the initial number of mixed samples was set to 100,000 and then increased in increments of 10,000 up to 300,000, resulting in 21 candidate sample libraries with different size levels. To reduce the influence of randomness introduced by endmember sampling and abundance assignment, five independent mixed-sample libraries were generated at each sample-size level for subsequent model training and accuracy evaluation.

3.2.2. Machine-Learning-Based Regression Unmixing Model Training

Given the high dimensionality, temporal dependence, and nonlinearity of the input data, Extreme Gradient Boosting (XGBoost) was selected as the unmixing model. Compared with traditional linear models, XGBoost does not rely on strict linear assumptions and is better suited to high-dimensional features, multicollinearity, and local noise. It also provides strong predictive accuracy, robustness, and computational efficiency.

The full-year spectral-temporal features of the mixed samples were used as model inputs, and the corresponding endmember abundances were used as supervisory labels. Because mixed-pixel unmixing is essentially a multi-output regression problem, whereas a standard XGBoost regressor predicts only a single target variable, a collaborative multi-regression strategy was adopted [27]. Specifically, all regressors shared the same input feature space, while an independent regressor was trained for each endmember. During prediction, non-negative truncation and normalization were applied to the outputs of the independent regressors so that the final abundance estimates satisfied both the non-negativity and sum-to-one constraints.

Model training was conducted using the mixed-sample database at different sample-size levels. For each candidate sample library, the data were split into training and validation sets at a ratio of 7:3. One independent regression model was trained for each endmember [37], and the training process was repeated five times to reduce random bias. To optimize model performance, the key hyperparameters of the XGBoost regressors were

tuned using a grid-search strategy based on the training dataset. The optimal hyperparameter combination was then used for subsequent model training and regional abundance unmixing. The candidate ranges and selected values of the key hyperparameters are provided in Supplementary Table S2. Model performance was evaluated using the coefficient of determination (R^2) and root mean square error (RMSE).

3.2.3. Subpixel Mapping of Flammable Tree Species

Because the mixed samples were generated across 21 sample-size levels, and five sample libraries were independently constructed at each level and used to train five regression models, each sample-size level corresponded to 25 unmixing models. Before mapping, the model groups at different sample-size levels were compared in terms of average accuracy and training efficiency. Model accuracy was considered the primary criterion. When the improvement in average prediction accuracy relative to the preceding sample-size level was no greater than 0.5%, while the training time continued to increase markedly, the model was considered to have reached a practical saturation point. The corresponding model group was selected for subsequent abundance mapping. During the mapping stage, the preprocessed annual Sentinel-2 regular time-series data were used as input. For each pixel, the multiband temporal reflectance and vegetation index features were organized into a feature vector in the same order as in model training and then input into the optimal model group for pixel-wise prediction. To reduce the random bias introduced by sample generation and model training, an ensemble strategy was used to average the predictions of the model group.

The model produced seven subpixel abundance fraction maps, with pixel values ranging from 0 to 1 to represent the relative proportions of the seven endmembers within each mixed pixel. Based on these abundance estimates, pixel types were further determined. Pixels with more than 90% non-forest and shadow abundance were classified as non-forest; otherwise, they were considered forest. For forest pixels, stand type was determined according to species abundance proportions. Pixels with more than 90% abundance of a single tree species were defined as pure stands, whereas the dominant type of the remaining pixels was identified according to the maximum-abundance principle. This process generated the final flammable tree-species distribution map for the study area. To reduce local classification noise, a conservative spatial post-processing procedure was subsequently applied to the derived categorical map. Only isolated pixels and fragmented patches smaller than 200 m² (equivalent to two 10 m × 10 m pixels) were considered for correction when their categories were inconsistent with the dominant class of the surrounding spatial neighborhood. Continuous patches, major stand boundaries, transitional zones, and spatial abundance gradients were preserved. Importantly, this procedure was applied only to the categorical map, while the original continuous abundance maps remained unchanged.

3.2.4. Accuracy Assessment of the Mapping Result

Mapping accuracy was assessed using the NFI data as reference. Because the outputs of this study included both stand structure information (pure vs. mixed stands) and dominant tree-species classes, a hierarchical validation strategy was adopted to evaluate reliability in terms of two aspects: mixed-type identification and species-type recognition. Validation samples were randomly drawn from the mapping results. Specifically, 10,000 points were randomly selected from pure-stand pixels and mixed-stand pixels, respectively, and then overlaid with NFI polygons to extract the corresponding forest type, dominant species, and species composition information. To reduce uncertainties caused by edge mixing and boundary displacement, sample points were restricted to valid NFI forest polygons, and

points located near polygon boundaries, in areas with missing attributes, or in areas with an obvious risk of spatial mismatch were excluded.

The ability to distinguish pure from mixed forest pixels was evaluated using the forest-origin attribute in the NFI polygons. A prediction was considered correct when the stand category of the validation point matched the corresponding NFI record. Based on this rule, the identification accuracies of pure and mixed stands were calculated. Species recognition accuracy was then assessed by comparing the mapped species class of each validation point, including pure-stand species and dominant species in mixed stands, with the species composition recorded in the NFI polygons. The confusion matrix was constructed to evaluate the classification performance for the five target flammable tree species.

4. Results

4.1. The Effect of Mixed Sample Size on Deconvolution Accuracy and Computational Efficiency

Figure 2a–e systematically illustrates the effects of training sample size on model unmixing accuracy and computation time across five random mixing scenarios. Overall, the models achieved relatively high unmixing accuracy under all scenarios. Among them, Mixed 2 performed best, with a maximum R^2 of 0.821. In terms of training time, computation increased significantly as the sample size expanded from 100 K to 300 K, showing an approximately linear growth trend. The maximum training time reached 98 min.

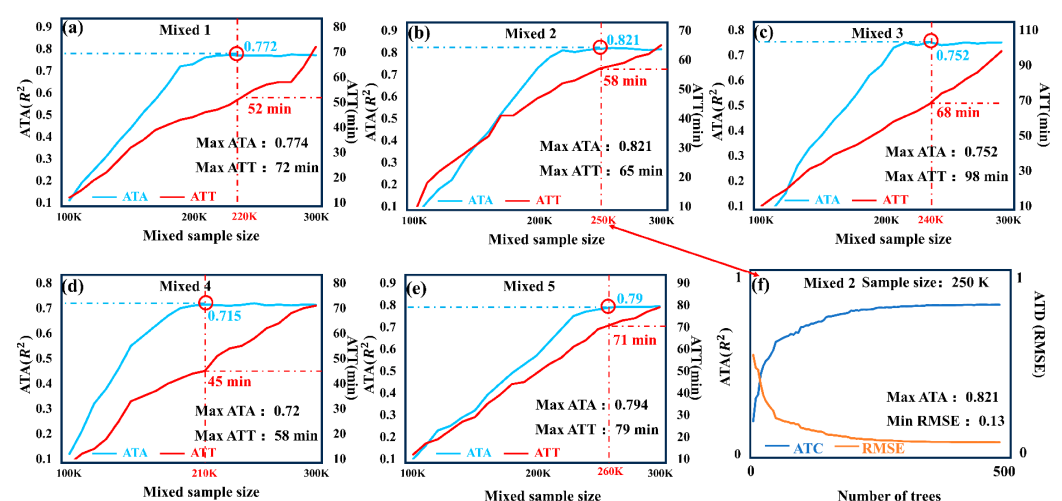


Figure 2. Average accuracy and training efficiency of the endmember abundance prediction models. Panels (a–e) show the trade-off between average prediction accuracy and training efficiency of the model groups under different sample sizes, whereas panel (f) illustrates the changes in fitting accuracy and fitting error of the best-performing model group during the iterative process. ATA denotes average prediction accuracy, ATT denotes average training time, and ATD denotes average prediction deviation.

A joint evaluation of accuracy and efficiency shows that model accuracy gradually improved with increasing sample size, but training cost rose sharply. Beyond the 200–250 K range, the improvement in average prediction accuracy was no greater than 0.5%, whereas the training time continued to increase markedly. Accordingly, the Mixed 2 model group trained with 250 K samples was selected for subsequent abundance mapping because it provided an appropriate balance between predictive accuracy and computational efficiency. This model achieved the highest accuracy ($R^2 = 0.821$) while maintaining an acceptable training cost. Further analysis of the optimal model group (Figure 2f) showed that, as the number of base learners (tree model) increased, prediction accuracy improved rapidly and then gradually stabilized, while RMSE decreased simultaneously and converged to a low

level, with a minimum value of 0.13, corresponding to an abundance-estimation error of approximately 13 percentage points on the normalized 0–1 scale.

4.2. Subpixel Mapping Results of Flammable Tree Species

Figure 3 presents the subpixel abundance prediction results for flammable forest stands in Yajiang County and the corresponding dominant-type classification map. Overall, the abundance maps effectively captured the continuous transitions among flammable stands, stands dominated by other tree species, and non-forest land. The results provide detailed information on the relative proportions of different components within individual pixels. Flammable stands were mainly distributed continuously across the central and northern mountainous areas of the study region, with locally high-abundance clusters occurring in some valleys and foothill zones. Flammable tree species accounted for more than 50% of the total forest area. In contrast, stands dominated by other tree species exhibited a mosaic-like distribution and, together with flammable stands, formed a complex mountainous forest landscape.

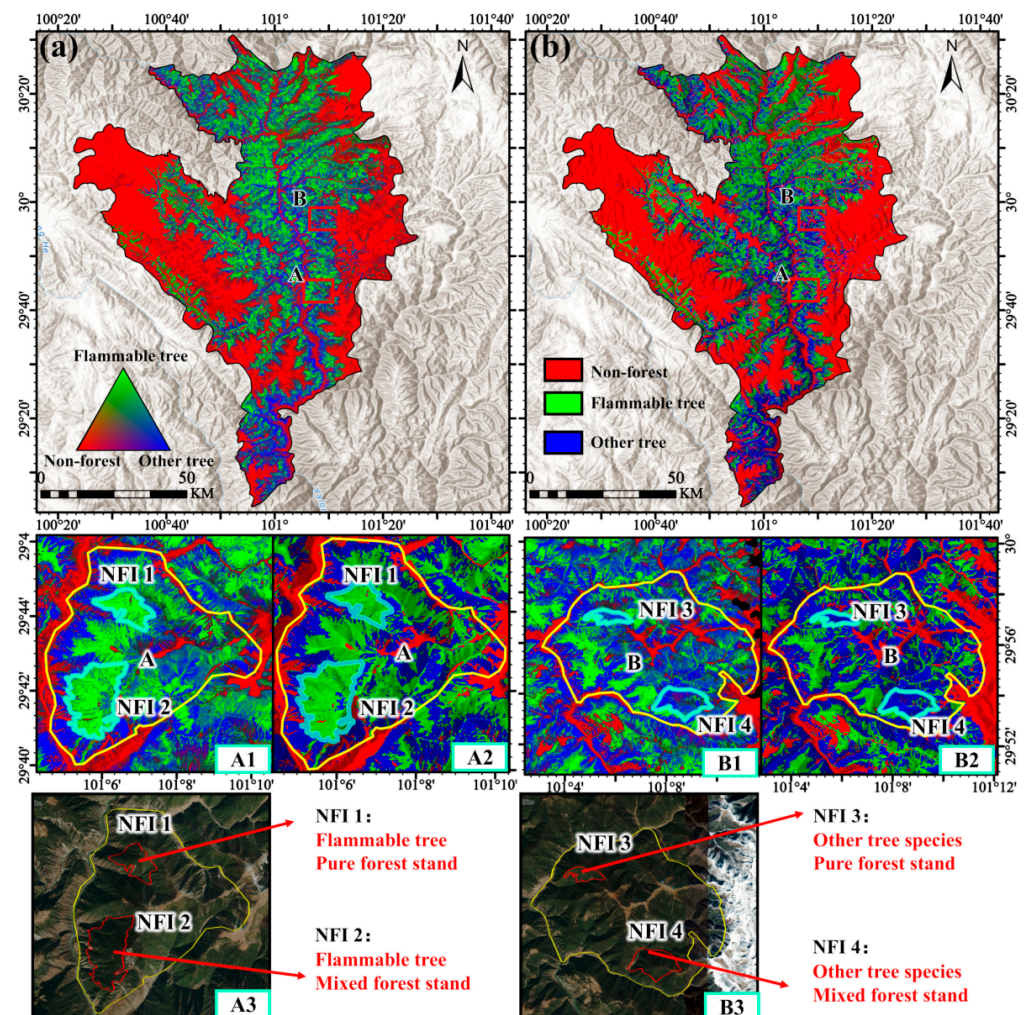


Figure 3. Abundance prediction results for flammable forest in Yajiang County. (a) Subpixel mapping results; (b) dominant-type distribution derived using the maximum-abundance rule. (A1–B3) show, respectively, the abundance prediction results (A1,B1), dominant-type distribution (A2,B2), and high-resolution satellite imagery (A3,B3) for representative sample areas under a detailed view.

At the local scale, the prediction results for two representative subregions in Figure 3 further demonstrate the spatial representativeness of the subpixel mapping results. In Area A, the abundance predictions clearly captured differences in the proportions of

flammable tree species within the stands corresponding to NFI 1 and NFI 2. The associated dominant-type classification results were generally consistent with both high-resolution satellite imagery and the NFI stand boundaries. Similarly, in Area B, the abundance maps accurately distinguished pure stands of other tree species from mixed stands, and the distribution of areas dominated by other species in the dominant-type map agreed well with the reference stand information.

Figure 4 further presents the subpixel abundance prediction results for the five flammable tree species and the dominant-species classification derived using the maximum-abundance rule. Overall, the different species exhibited clearly differentiated spatial distribution patterns across the study area. Spruce was mainly distributed in the northern part of the study area and on shady, moist slopes at middle to high elevations, with a relatively scattered pattern. Mountain oak was concentrated in the central and southern parts of the region and generally showed patchy and belt-like characteristics. Mountain pine had the widest distribution and formed continuous belts in the central mountainous area, making it the most dominant flammable tree species. In contrast, birch and fir occupied relatively smaller areas and mainly occurred as localized clustered patches, with birch appearing more frequently in local mountain transition zones. According to the dominant-species map, spruce, mountain oak, mountain pine, birch, and fir accounted for 5.0%, 14.4%, 22.0%, 6.1%, and 9.5% of the mapped forest area, respectively, whereas other tree species accounted for 43.0%. Taken together, Figures 3 and 4 indicate that the subpixel mapping results preserved both component abundance information and dominant-type information, thereby effectively revealing the continuous spatial variation in flammable stands and their internal species composition across the study area.

4.3. Accuracy Assessment of the Flammable Tree Species Map Based on NFI Data

Validation against the NFI reference data showed that the subpixel mapping results for flammable tree species achieved high accuracy in both stand identification and species classification (Table 2; Figure 5). For stand-structure recognition, the identification accuracy reached 93.95% for pure-stand samples and 91.22% for mixed-stand samples. These results indicate that the model was able to effectively distinguish pure stands from mixed stands and had strong capability in identifying the internal mixing characteristics of forest pixels. For species classification, the identification accuracy was 87.28% for pure-stand species types and 84.41% for dominant species in mixed stands.

Table 2. Validation results of model identification accuracy based on NFI data.

Identification	Correctly Identified	Incorrectly Identified	Accuracy
Pure stands	9395	605	93.95%
Mixed stands	9122	878	91.22%
Pure-stand species type	8728	1272	87.28%
Dominant species in mixed stands	8441	1559	84.41%

According to the confusion matrices (Figure 5), the overall accuracy (OA) for pure-stand samples was 87.28%, with a Kappa coefficient of 0.84, whereas the overall classification accuracy for mixed-stand samples was 84.41%, with a Kappa coefficient of 0.80. These results indicate a high level of categorical agreement between the mapped dominant-species classes and the NFI reference data.

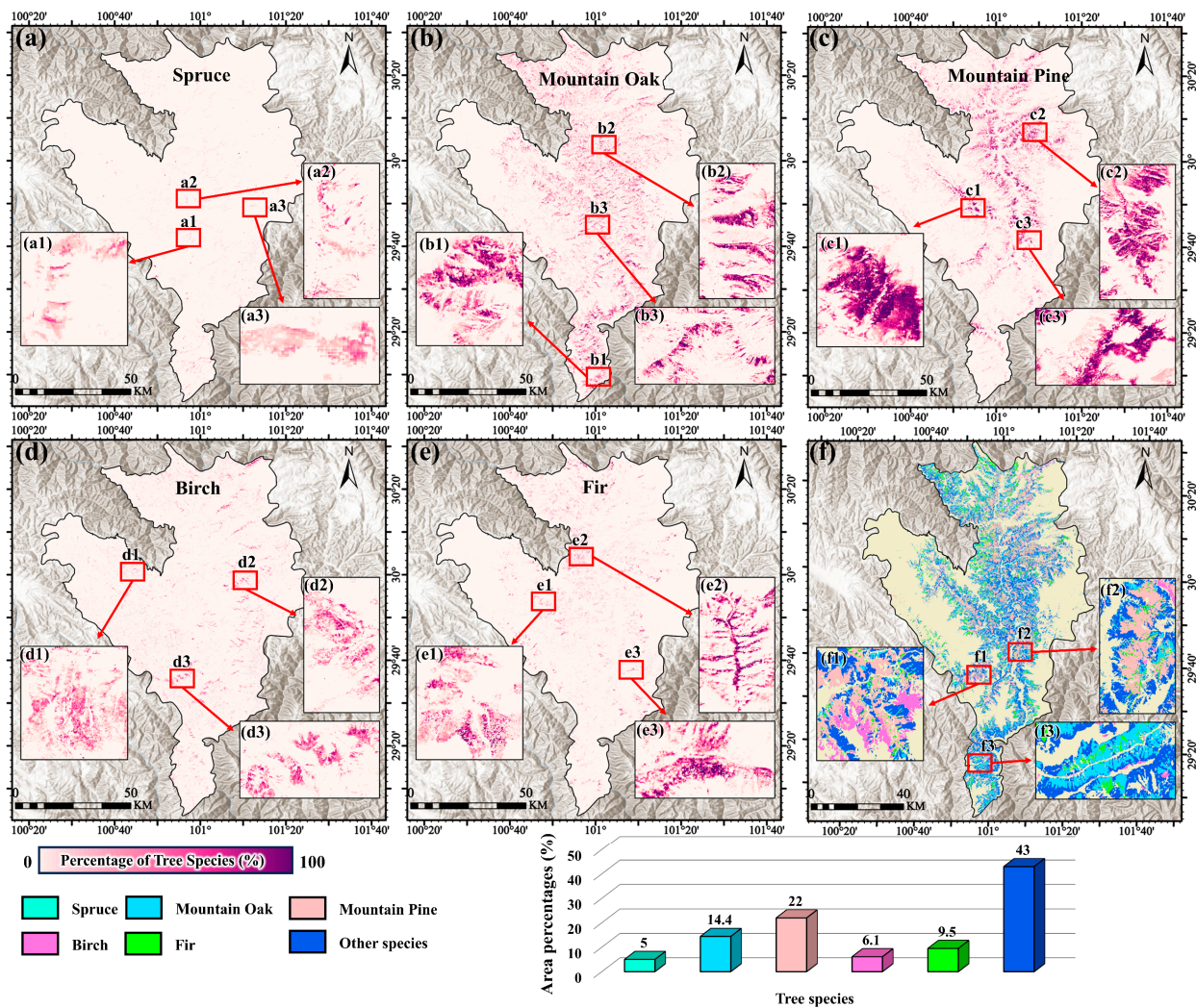


Figure 4. Abundance prediction results for each flammable tree species in Yajiang County and the dominant-category classification derived using the maximum-abundance rule. Panels (a–e) show the abundance prediction results for the five flammable tree species, and panel (f) shows the dominant-category classification result. Panels (a1–f3) show the clear magnified views of the example region abundance prediction results. SP, spruce; MO, mountain oak; MP, mountain pine; BI, birch; FI, fir; and OT, other species.

Under pure-stand conditions, both user's accuracy (UA) and producer's accuracy (PA) were generally high across most classes. Mountain pine showed the best performance, with UA and PA reaching 92.25% and 90.50%, respectively. Spruce, mountain oak, and fir also achieved relatively stable classification performance, with UA and PA values close to or above 80% in most cases. In contrast, birch showed lower accuracy, with a UA of 68.71%. Examination of the confusion matrix indicated that a considerable proportion of the errors were associated with confusion between the target flammable tree species and the "other tree species" class. This pattern suggests that the spectral heterogeneity of the composite "other tree species" category may introduce uncertainty into the interpretation of the corresponding abundance maps.

Under mixed-stand conditions, classification accuracies were slightly lower than those for pure stands but remained relatively stable overall. Mountain pine again achieved the best performance, with UA and PA values of 89.35% and 89.74%, respectively. Spruce reached a UA of 81.75% and a PA of 80.45%, whereas mountain oak achieved a UA of 85.82% and a PA of 77.82%. Birch and fir showed comparatively lower accuracies, with

UA values of approximately 65%. Classification errors were again mainly concentrated between the target flammable tree species and the “other tree species” class, as well as among spectrally similar coniferous species.

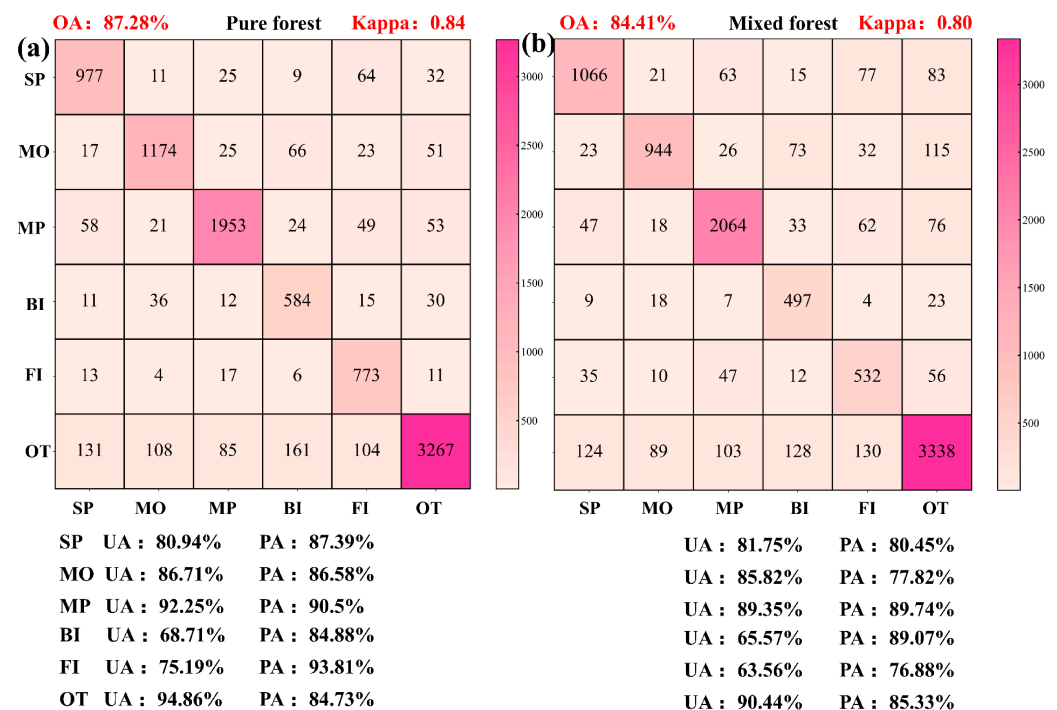


Figure 5. Accuracy assessment results for the flammable tree species distribution map. Panels (a) and (b) show the confusion matrices for pure-stand and mixed-stand validation samples, respectively. OA, overall accuracy; UA, user's accuracy; PA, producer's accuracy; SP, spruce; MO, mountain oak; MP, mountain pine; BI, birch; FI, fir; and OT, other species.

5. Discussion

5.1. Innovation of the Subpixel Mapping Framework for Flammable Tree Species

Tree species distribution in complex mountainous forests often exhibits pronounced spatial interspersion and scale dependence. Under medium-resolution remote sensing conditions, a single pixel commonly contains multiple tree components, understory background, bare ground, and shadow, making mixed pixels a major factor limiting the accuracy of forest tree-species mapping [38,39]. In this context, the spatial representation of flammable tree species should be understood as a continuous variation in the relative proportions of different species within individual pixels. Traditional hard-classification approaches are therefore insufficient for capturing the true coexistence of flammable and non-flammable tree species in complex stands, and they are also unable to characterize the continuous compositional transition between pure and mixed stands [40].

To address this issue, this study reformulated flammable tree-species identification as a problem of continuously estimating endmember proportions within mixed pixels, thereby shifting the methodological framework from discrete classification to continuous unmixing. Built on a limited number of high-quality pure samples, the framework systematically expanded the training data in abundance space through a temporal spectral mixing strategy, effectively alleviating the challenges of scarce pure samples and limited field observations in complex mountainous forests. Unlike methods that directly train classifiers using polygon labels, this study generated a large sample library with explicit abundance labels through controlled mixing, enabling the model to learn spectral-temporal response patterns under different compositional combinations and to establish a more continuous relationship

between species composition and remote sensing signals [24]. This design demonstrates the potential of using a limited set of endmember samples to support regional-scale subpixel mapping and provides a potentially transferable sample-construction strategy for fine tree-species identification in complex forest environments [14]. However, its transferability across different regions and years requires further validation.

5.2. Uncertainty in the Construction of the Mixed Spectral Database

Although this study constructed a large temporal mixed spectral database based on pure endmember samples and used it to support abundance unmixing, uncertainty remains in the sample-generation process itself, which may affect the consistency between training samples and real forest pixels.

Mixed samples were generated through random endmember selection and random abundance assignment, followed by non-negative truncation and normalization to satisfy basic compositional constraints. While this ensures numerical validity, it does not impose structural constraints among endmembers during mixing, such as species co-occurrence probabilities, habitat-dependent coexistence patterns, or the non-random spatial organization between tree species and background components. As a result, some synthetic samples may deviate from actual forest mixing mechanisms. Similar concerns have been noted in previous studies. For example, Bolyn et al. [7] suggested that the abundance relationships learned from synthetic mixtures may be closer to an “idealized mixing space.” In real forests, however, species coexistence is often shaped by ecological niche differentiation and habitat dependence. Therefore, purely random abundance combinations may overrepresent uncommon mixtures while underrepresenting ecologically frequent ones.

Additional uncertainty arises from the limited representativeness of the endmember samples. In this study, a deliberately compact endmember library was constructed to examine whether the proposed framework could achieve reliable abundance estimation under constrained reference-data conditions, which are common in regional forest applications. Rather than maximizing sample quantity, priority was given to spectral purity and sample quality. Candidate endmembers were selected from internally homogeneous NFI polygons, buffered from polygon boundaries, and further checked using high-resolution imagery to exclude pixels affected by roads, exposed understory, or severe terrain-shadow contamination. The relatively high mapping accuracy obtained under this limited-sample setting supports the feasibility of the proposed framework, although it should not be interpreted as evidence of universal transferability.

The “other tree species” class was represented by only 100 samples in total. Compared with the target flammable tree species, this class is inherently a highly heterogeneous composite category, potentially including multiple species combinations with different canopy structures and phenological characteristics. Although compressing such complex information into a single endmember class is operationally necessary for regional-scale mapping, it inevitably increases within-class spectral variability and may weaken the discrimination boundary between this class and the target flammable species. As a result, the risk of confusion with spectrally similar species, such as spruce, mountain oak, and fir, is increased. This is also consistent with the cross-confusion observed between some flammable tree species and other tree species in the subsequent accuracy assessment (Figure 5). Hemmerling et al. [14] also noted this issue, arguing that when a category contains substantial interspecific or environmental-gradient variability, modeling it under a single class label tends to inflate within-class variance and reduce classification stability for marginal and transitional types.

Future work could address this limitation by subdividing the “other tree species” class into several ecologically meaningful and spectrally consistent subclasses; separating back-

ground components according to topographic, illumination, and land-cover conditions; and extending endmember coverage across broader environmental and phenological gradients. These refinements would improve the representativeness of the endmember library and enhance the robustness of abundance estimation in complex mountainous forests.

Terrain-induced illumination differences represent an additional source of uncertainty. Variations in slope and aspect may alter the reflectance of the same tree species, increase within-class spectral variability, and affect abundance estimation. Although pixels affected by severe terrain shadows were excluded during endmember screening and shadow was included as a background component, these measures cannot fully eliminate topographic effects. Future work should integrate topographic correction and terrain-stratified end-member sampling to improve model robustness.

5.3. Potential Errors in the Accuracy Assessment of the Mapping Results

Although the mapping results for flammable tree species were systematically validated against the NFI reference data and achieved relatively high overall accuracy, potential bias arising from internal heterogeneity within NFI polygons should not be overlooked. While the NFI provides an important reference for regional forest mapping, its attributes are generally recorded at the polygon level and therefore cannot fully capture fine-scale spatial heterogeneity within individual stands. In complex mountainous forests, even a polygon recorded as a pure stand may still contain patches or edge zones with other tree species. Similarly, a polygon labeled with a dominant species may also include a certain proportion of mixed components that are not reflected in the attribute fields. Under such circumstances, when the model identifies tree-species components at specific locations that differ from the polygon record but may in fact exist in reality, these predictions are still treated as classification errors during validation, which can lead to an underestimation of mapping accuracy. This issue is likely to be especially relevant in the present study because the model outputs emphasize pixel-level compositional information, whereas the NFI provides generalized stand-level attributes; thus, the two differ in their spatial representation scales. For species such as mountain oak, mountain pine, and fir, which often show strong local interspersions, pixel-level predictions may be more sensitive than polygon-level records in capturing subtle within-stand variation. Therefore, some apparent classification errors may actually reflect limitations of the reference data in describing internal stand heterogeneity. Previous studies [7,25] have suggested that this problem could be alleviated by integrating higher-resolution imagery, UAV observations, or field survey data to supplement the internal composition of NFI polygons, thereby improving the representation of pixel-scale heterogeneity in the reference data. This will also be an important focus of our future work.

6. Conclusions

This study developed a subpixel mapping framework for flammable tree species in Yajiang County, Sichuan Province, by integrating Sentinel-2 time-series data with a spectral mixing–unmixing strategy. The framework was designed to characterize within-pixel species composition under the mixed-pixel conditions commonly encountered in medium-resolution remote sensing imagery. The main conclusions are as follows:

- (1) By constructing temporal mixed samples from pure endmembers and integrating them with an XGBoost-based collaborative multi-regression framework, the proposed method achieved stable abundance-retrieval performance on synthetic mixed samples with known fractions. The optimal model was obtained under the Mixed 2 dataset with 250 K samples, reaching an R^2 of 0.821.
- (2) The resulting maps provided a spatially explicit representation of the composition and dominant-species patterns of flammable forests in Yajiang County. Flammable

- tree species accounted for more than 50% of the mapped forest area and were mainly concentrated in the central and northern parts of the study area. Among the five target species, mountain pine was the most widespread dominant species, followed by spruce and mountain oak, whereas birch and fir exhibited more localized distributions.
- (3) The NFI-based categorical assessment supported the reliability of the mapped stand-structure and dominant-species patterns. The identification accuracies for pure and mixed stands were 93.95% and 91.22%, respectively, while the classification accuracies for pure-stand species types and dominant species in mixed stands were 87.28% and 84.41%, respectively. These results demonstrate strong categorical consistency between the mapped results and the NFI records.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs18121952/s1>.

Author Contributions: Conceptualization, Z.L., Y.W., L.W., W.Y., B.D. and B.Y.; Methodology, Z.L., X.D., D.D., L.W. and B.Y.; Software, Z.L., X.D., L.W. and B.Y.; Validation, Z.L., L.W., B.D. and B.Y.; Formal analysis, Z.L., D.D., W.Y., B.D. and B.Y.; Investigation, Z.L., X.D., D.D., Y.W., W.Y., B.D. and B.Y.; Resources, Z.L., X.D., D.D., Y.W., B.D. and B.Y.; Data curation, Z.L., X.D., L.W., B.D. and B.Y.; Writing—original draft, Z.L., D.D., Y.W., L.W., W.Y. and B.Y.; Writing—review & editing, Y.W., W.Y. and B.Y.; Visualization, Z.L., X.D. and B.Y.; Supervision, X.D. and B.Y.; Project administration, Y.W., L.W. and B.Y.; Funding acquisition, D.D., Z.L. and L.W. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported in part by the Sichuan Science and Technology Program (Research on Precise Identification of Forest Fire Risks for Distribution Lines of 35 kV and Below Crossing Forest Areas), in part by the Basic Research Project of Sichuan Academy of Forestry Sciences (Grant No. 2026JBKY21), in part by the Department of Forestry of Guangxi Zhuang Autonomous Region (Grant No. 2023GXZCLK20), and in part by the Department of Science and Technology of Guangxi Zhuang Autonomous Region (Grant No. GXKJAA 24263019-2).

Data Availability Statement: The data are not publicly available due to privacy restrictions.

Acknowledgments: We thank the reviewers for their thoughtful comments and constructive suggestions, which substantially improved this manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

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