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Large-Scale Mapping of Complex Forest Typologies Using Multispectral Imagery and Low-Density Airborne LiDAR: A Case Study in Pinsapo Fir Forests

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Abstract: Climate change increases the vulnerability of relict forests. To address this problem, regional Forest Services require silvicultural and conservation actions to designate specific forest management alternatives. In this context, the main objective of this study was to develop a methodology to map complex *Abies pinsapo* forest typologies using multispectral and low-density airborne LiDAR data and machine learning. Stand density, species composition and cover were used to identify seven forest typologies. Random forest resulted as the more accurate model (OA = 0.62; Kappa = 0.43) to classify those types based on multispectral and LiDAR data, although showing a moderate model performance. Classification performance showed great differences between forest types with better results for the uneven-aged stands compared to the even-aged and two-aged stands. The developed typology was applied to supply local forest managers with more accurate forest maps that can be used to improve forest management plans. The typology proposed is easy to apply in forest management practices since it only uses as input the diameter at breast height, tree density and specific composition. The study demonstrated the potential of low-density LiDAR data combined with spectral information from high-resolution orthophotos to predict the structural characteristics of complex forest typologies.

Keywords: climate change adaptation; forest management; forest typology; remote sensing; machine learning

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1. Introduction

Forest ecosystems provide critical and diverse productive and ecosystem services to human society [1] such as wood, carbon storage and biodiversity [2,3]. However, the future of forests is uncertain as a consequence of different factors such as illegal logging and, in particular, climate change [4] due to increasing temperatures and extreme droughts in many regions of the world [5], but especially in the Mediterranean regions [6]. Mediterranean forest ecosystems face substantial climate risks that could trigger an increase in areas affected by large fires and forest dieback events [7,8]. Mediterranean firs (*Abies* species) constitute a relevant example of an endangered forest ecosystem highly vulnerable to climate risks [9]. *Abies pinsapo* Boiss. is a climate-relict fir species, endemic to the south-west of the Iberian Peninsula [10]. This species occupies a rather unique and limited ecological habitat leading to higher extinction risk [11], and it is included in the International Union for Conservation of Nature (IUCN) Red List of Threatened Species as an endangered species [12]. In recent decades, its distribution range has been under climatic risks in some areas, with climate change one of the main threats to its conservation [13–15]. For example, in the protected areas of Sierra de las Nieves-Grazalema-Los Reales de Sierra Bermeja (hereafter SN, SG and SB, respectively), pinsapo fir populations are declining [15]. Thus, there is an urgency to implement mitigation and adaptation measures that could help pinsapo fir forests cope with the threats of climate change, habitat degradation and invasive species [16].

In this sense, forest structure definitions (forest typologies) can assist in outlining adaptation priority regions [17]. Description of forest typologies may include measures of species composition, diversity, tree height, stem diameter, basal area, tree density and the age class distributions and spatial distribution patterns of the component species in the forest [18]. Their characterization is usually performed by direct in-field measurements (traditional forest inventories) [19]. National and local forest inventories represent fundamental support for establishing forest management strategies due to their extent and the large number of plots and variables that are sampled [20]. However, these forest inventories are often limited in temporal scope and spatial scale.

In recent years, new approaches combining forest inventory field plots and remote sensing data have emerged to improve forest characterization and mapping [21]. Advanced remote sensing technologies provide data to support the subsequent development and parameterization of models for an even broader range of information needs. Several examples can be found where field data and different sources of remote sensing were used to identify forest typologies [17]. For instance, multispectral imagery has been successfully used in forest type classification and mapping, commonly through supervised classifications or decision rules [22]. However, measures of vertical forest structure, which define the most important variables for predicting forest typologies, cannot be readily derived from multispectral imagery. To overcome this limitation, methods have been sought to integrate this information with other remote sensing data, particularly with LiDAR (Light Detection and Ranging). LiDAR is an active remote sensing technology capable of measuring the 3D distribution of vegetation within forest canopies. For example, Aerial Laser Scanning (ALS) data from the Spanish National Plan for Aerial Orthophotography (PNOA) have yielded good results for monitoring attributes related to vertical and horizontal forest structures [23,24]. However, the ability to identity forest typologies with remote sensing data is often limited due to physical constraints such as high canopy closure and the presence of multiple vegetation layers. For this reason, although there is extensive literature concerning the use of ALS data in forest science under different approaches and experimental designs, there is a lack of studies that extend the use of ALS data to predict forest typologies in complex environments (but see [17]). These issues call for new approaches based on multisource remote sensing and advanced classification algorithms.

Motivated with the above limitations, we used pinsapo fir forests as study cases to improve the applicability of relevant forest typologies based on remote sensing data. Pinsapo fir forests exhibit complex structural forms, and they also show some affinity for mixed and ecotonal forests, which results in horizontal and vertical heterogeneity [25] (see Figure 1). Currently, several typologies have been proposed for this species according to phytogeography [11,26–28], large chorological zones [10,29] and physiognomic aspects [30]. The lack of standardization of typologies for complex forest structures makes it difficult to cross-reference map products and therefore to validate products and to monitor forest stands for a long period. Also, the effectiveness of these typologies varies significantly among methodologies and applications, leading to concerns about their general application for both conservation and climate change adaptation objectives. These gaps often result from a lack of data with enough temporal recurrence, as observed in studies such as [31].

Therefore, in this study, the main objective was to develop a forest typology for pinsapo fir forests based on forest composition and structural attributes and mapping of this typology using low-resolution LiDAR and multispectral data. The specific objectives of this study were (i) to develop a forest typology classification based on traditional forest inventory metrics and (ii) to use remote sensing data to spatialize the results at a large scale and improve the applicability of the classification. Our approach considers species–area distribution and complex structures, and it aims to generate a map of existing pinsapo fir forests while the identification of priority sites for conservation, restoration and legal protection is currently lacking. This study serves as an application of a spatial robust remote sensing-based approach to develop forest typologies of complex Mediterranean forests.

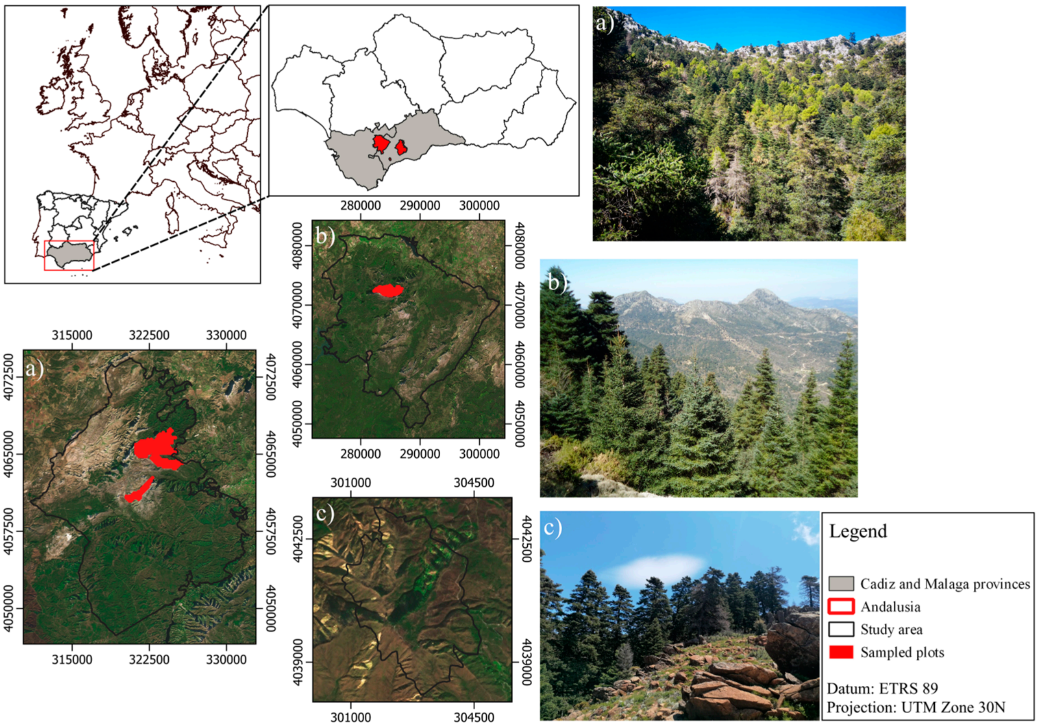

Figure 1. Location of the study area and sampled plots (n = 694; red marks on bottom inserts). A map showing the natural distribution of *Abies pinsapo* Boiss. in Andalusia (upper insets) with red polygons (upper right inset) indicating the study area at (**a**) Sierra de las Nieves; (**b**) Sierra de Grazalema; and (**c**) Los Reales de Sierra Bermeja. Photographs correspond to a mixed stand of *A. pinsapo* with Pinus species in SN (**a**); pure stand of *A. pinsapo* in SG (**b**); and pinsapo fir forests on peridotites in SB (**c**). Graphs were generated by QGIS 3.26.3 (https://www.qgis.org, accessed on 19 August 2024) with the global vector data from the GADM database (https://gadm.org, accessed on 19 August 2024).

2. Materials and Methods

2.1. Study Area

The study area is located in the southern part of Andalusia (Figure 1) within the natural distribution of *Abies pinsapo* in the Iberian Peninsula according to the Spanish Forest Map [32]. The pinsapo fir forests occur in three locations (SN, SG and SB), covering a total area of 4973.9 ha. The climate in the study area is Mediterranean, with a summer drought period that extends into the fall. Most of the precipitation occurs in winter and spring, with a mean annual rainfall between 600 and 1600 mm. The mean annual temperature ranges from 8 °C to 18 °C. The summer months are mild with an average maximum daily temperature of the warmest month (August) between 29 °C and 33 °C, with infrequent summer precipitation from thunderstorms. The soils are composed of limestone in SG and SN and peridotites in SB [33].

2.2. Methodological Framework

Our study used several datasets and required the development of remote sensing predictors and data analysis procedures. A flowchart outlining the steps and relationships of each process is provided in Figure 2.

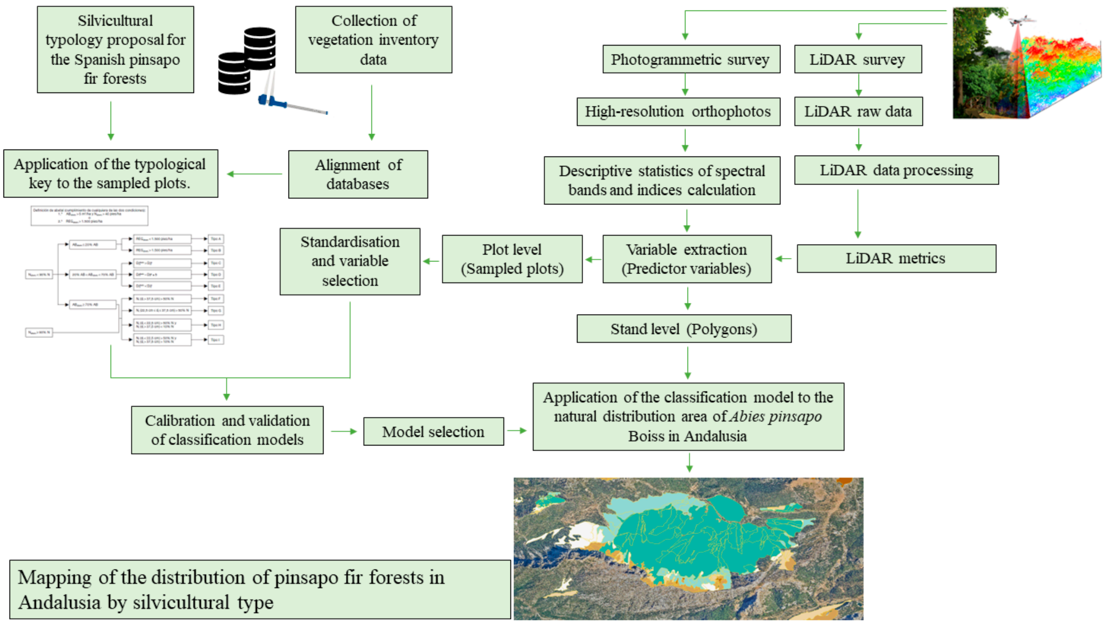

Figure 2. Main workflow diagram for large-scale mapping of pinsapo fir forest typologies. Response variables were extracted from the vegetation inventory data.

2.3. Proposed Typology of the Pinsapo Fir Forests

The proposed typology was elaborated partially based on previous proposals that have been made for the species [11,26,28,30] and other silvicultural typologies proposed for *Abies alba* Mill. forests [31]. The typification of the pinsapo fir forests aims to describe forest types that (i) can be classified in a simple way on the basis of integrating previous cartography and open remote sensing data; (ii) enable easy field interpretation; (iii) have an ability for current and future silvicultural conditions and; (iv) are useful as decision-support tools in forest management plans. Based on these criteria, eleven different types of pinsapo fir forests were identified (Table 1).

Table 1. Summary table of the proposed forest typology for pinsapo fir forests.

Class	Type	Subtype	Definition
I	0		Isolated trees of *A. pinsapo*
	1		Open forests of *A. pinsapo* and isolated stands
	2		Recent reforestations
II	0	a	Even-aged pure stands of *A. pinsapo*
		b	Two-aged pure stands of *A. pinsapo*
		c	Uneven-aged pure stands of *A. pinsapo*
II	1	a	Even-aged mixed stands with *A. pinsapo*
		b	Two-aged mixed stands with *A. pinsapo*
		c	Uneven-aged mixed stands with *A. pinsapo*
III	0		Stands of other species with dominance of *A. pinsapo* in the stages of stand development * of pre-thicket and thicket. (dbh < 7.5 cm).
	1		Stands of other species with dominance of *A. pinsapo* in the stage of stand development of polewood. (7.5 cm < dbh < 10 cm).

* Stage of stand development: each of the stages of development of a tree also apply to groups in which there is a certain morphological and functional uniformity. The natural age classes established in Spanish forestry, in order, are upgrowth, pre-thicket, thicket, low polewood, high polewood, low timber stage, middle timber stage and high timber stage [34].

To correctly classify pinsapo forest stands based on this forest typology, we developed a robust hierarchical classification criterion based on forest inventory field plot information (Figure 3). Specifically, we followed four main inventory metrics: (a) canopy cover, (b) proportion of number of trees of pinsapo, (c) stage of stand development [34] and (d) age class structure.

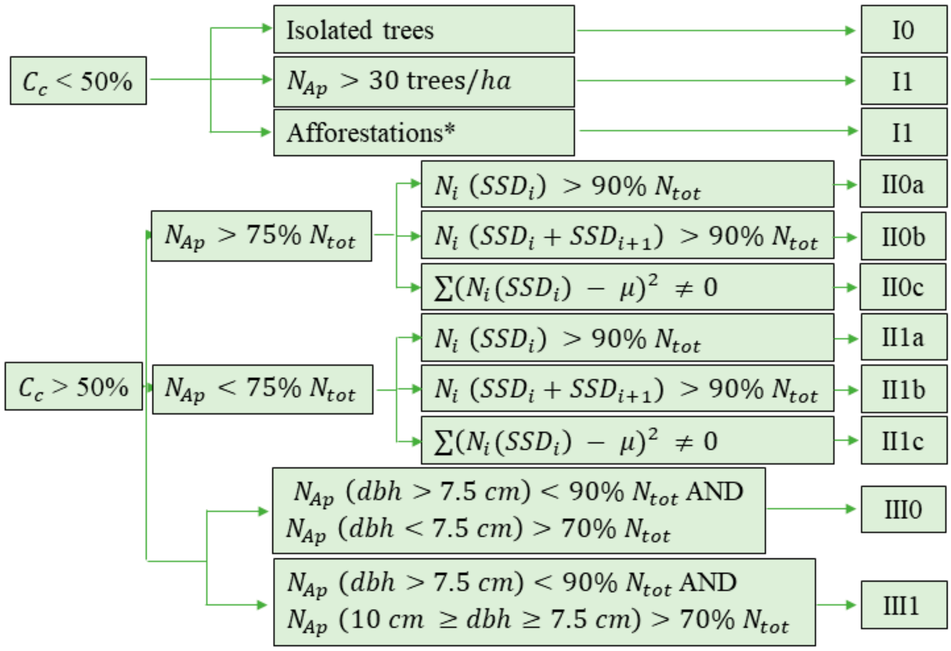

Figure 3. Criteria of the eleven types of pinsapo fir forests. Cc: canopy cover. NAp: number of trees of *Abies pinsapo*. Ntot: total number of trees. SSD: stage of stand development. Dbh: diameter at breast height. * This type can only be identified through expert knowledge.

2.4. Data Collection

2.4.1. Field Data

The typology proposed was applicated on quantitative information supplied by local forest inventories. A network of 694 circular plots was collated at the intersections of a 200 × 200 m UTM grid for *Pinus* spp. forests and 167 × 167 m for pinsapo fir forests with radii of 13 m (Supplementary Material Table S1). On each plot, all trees with diameter at breast height (dbh) > 2.5 cm were measured.

2.4.2. LiDAR Data

Airborne Laser Scanning (ALS) data were provided in *.laz* format, and each file comprised a square tile of 2 × 2 km (data are publicly available at: https://centrodedescargas.cnig.es/CentroDescargas/, accessed on 15 May 2023). The study area was surveyed in 2020, with an average point density of 1.5 pulses m^{-2}. The reference system employed was the European Terrestrial Reference System 89 (ETRS89) and UTM coordinate system. We assumed accurate georeferencing during postprocessing and carried out no further co-registration.

2.4.3. Multispectral Information

We used orthophotos captured in 2020 by the National Plan of Aerial Orthophotography (PNOA) of the Spanish National Geographic Institute (IGN) (data are publicly available at: https://centrodedescargas.cnig.es/CentroDescargas/, accessed on 15 May 2023). The four-band images (RGB + NIR) had a geometric resolution of 25 cm and a planimetric RMSE $\leq$ 50 cm.

2.5. Forest Typology

2.5.1. Field Data Processing

In the first step, variables with a higher forest structural relevance were selected: basal area (ba, $m^2\ m^{-2}$), individual diameter at breast height (dbh, cm) and stand density (N, trees ha^{-1}). Then, all wood individuals of each plot were grouped according to the stage of stand development (i.e., regeneration, sapling and adults). Next, the proportion of trees of each species with respect to the total trees on the plot was calculated and related to species composition for classification into pure and mixed stands. Based on these data, each plot was assigned according to the forest typology criteria (Table 1, Figure 3).

2.5.2. LiDAR Data Processing

Once forest typologies were assigned for each plot according to field variables, predictor variables based on remote sensing data were calculated at the plot scale. Two different groups of variables were initially selected. First, variables reflecting stand vertical structures based on their particular internal stratification were extracted from ALS data.

ALS data were processed using a combination of FUSION LDV 3.80 [35] and LAStools v180520 software [36]. Raw ALS point clouds were converted into several intermediate products: a DEM (Digital Elevation Model), normalized point clouds and a CHM (Canopy Height Model). This was conducted by first cleaning the noise from the point clouds. ALS points were classified as ground and non-ground (vegetation) returns using a morphological filter. The metrics (e.g., mean, mode, standard deviation), interquartile distance (IQ) and percentiles were then calculated from the height distribution of laser returns by employing the *lasheight* tool. The *CloudMetrics* tool was used to derive a suite of ALS canopy metrics (n = 47). A complete description of ALS-derived LiDAR metrics can be found in [35] and the Supplementary Materials.

2.5.3. Spectral Data Processing

Second, predictive variables referring to stand species mixtures were obtained from multispectral images. Visual bands (RGB; red, green and blue) and near-infrared (NIR) were used to obtain these predictive variables (Table 2).

Table 2. Statistics generated from the spectral information for large-scale mapping of pinsapo fir forest typologies.

Statistics	
Arithmetic mean of the values of *n* cells	Variance: mean of the squared differences of *n* cells with respect to their arithmetic mean
Maximum: maximum value of *n* cells	Coefficient of variation: relationship between the size of the mean and the variability of the variable
Minimum: minimum value of *n* cells	Interquartile range: difference between the third and first quartile of a distribution
Standard deviation: square root of the cell variance	Sum: sum of the values of *n* cells

2.5.4. Model Variable Selection

Selected predictive variables were standardized and resampled to a common scale with a mean equal to zero and variance equal to one, which eliminated the measurement and different variability of the original variables [37]. Then, given the large number of variables considered (Tables S1 and 2), selection of the variables was carried out by applying the VSURF (Variable Selection Using Random Forests) algorithm [38]. This algorithm is specially designed to obtain an importance ranking in databases with a high number of variables. In the first step, irrelevant variables were eliminated from the dataset. In the next step, response-related variables were removed for interpretation purposes, selecting the best set of variables for prediction purposes in the last step. Finally, a collinearity analysis was carried out on the selected variables to reduce uncertainty in the models' predictions. For this, a variance inflation analysis (VIF) was applied [39]. All variables with a VIF value > 10 were eliminated [40]. In this way, the dimensionality was reduced, without significant loss of information. The five variables selected were "Elev.P80" (80th percentile of elevation values), "Elev.MAD.mode" (median absolute deviation of the mode of elevation values), "Elev.variance" (dispersion or spread of elevation values), "Blue_stdev" (standard deviation of blue band values) and "Blue_mean" (arithmetic mean of the blue band values).

2.5.5. Models Calibration and Validation

For the classification of pinsapo fir forest types, three different non-parametric classification algorithms were used: Random Forest [41], Support Vector Machines (SVMs) [42] and Neural Networks [43]. The use of these algorithms in remote sensing studies has increased due to their ability to integrate different types of data [44]. To estimate the output error of the algorithms used, two sets of available observations (sampled plots) were randomly divided into a training set (70% of total observations) and validation data (remaining 30%). The model was fitted to the training set, and the fitted model was used to predict the responses for the observations in the validation set. Finally, the degree of reliability of the classification was evaluated for each of the three algorithms using a confusion matrix including overall accuracy (OA) and Kappa Index [45]. The value of this indicator ranges between 0 and 1, where 1 represents a perfect classification [46] (<0.2, poor; 0.21–0.40, weak; 0.41–0.60, moderate; 0.61–0.80, good; and 0.81–1.00, strong).

3. Results

3.1. Classification Models

The three algorithms used to classify pinsapo forest types showed similar accuracy (Table 3). The overall hit rate showed a percentage of correct predictions of ≈62%. This percentage of correct predictions was high, considering the elevated number of classes classified (7). However, the Random Forest classification algorithm showed the highest Kappa Index (k = 0.43). This value indicates a sample of "moderate" classification agreement.

Table 3. Accuracy assessment obtained for the different classification models for large-scale mapping of pinsapo fir forest typologies.

Model	Overall Accuracy	Kappa	Error Rate
Random Forest	0.62	0.43	0.38
Support Vector Machines	0.62	0.26	0.38
Neural Network	0.61	0.29	0.39

Across forest types, the RF algorithm classified the uneven-aged stand typologies (II0c and II1c) better but slightly underperformed to differentiate between even-aged and two-aged stand types (Table 4). These were the most confusing types, with a higher number of false positives and false negatives.

Table 4. Accuracy assessment for different pinsapo fir forest types for large-scale mapping of pinsapo fir forest typologies (see Table 1 and Figure 3 for type description).

Type	II0a	II0b	II0c	II1a	II1b	II1c	III1
Sensitivity	0.25	0	0.59	0.08	0	0.81	0.31
Specificity	0.99	1	0.79	0.99	1	0.52	0.79
Detection rate	0.05	0	0.20	0.05	0	0.41	0.48

3.2. Variable Importance for Pinsapo Fir Forest Types Classification

From the predictors used in the classification, the LiDAR metrics “Elev.P80”, “Elev.MAD.mode” and “Elev.variance” had the highest predictive power, followed by two statistics calculated from the blue band of the PNOA aerial orthophotographs (Figure 4).

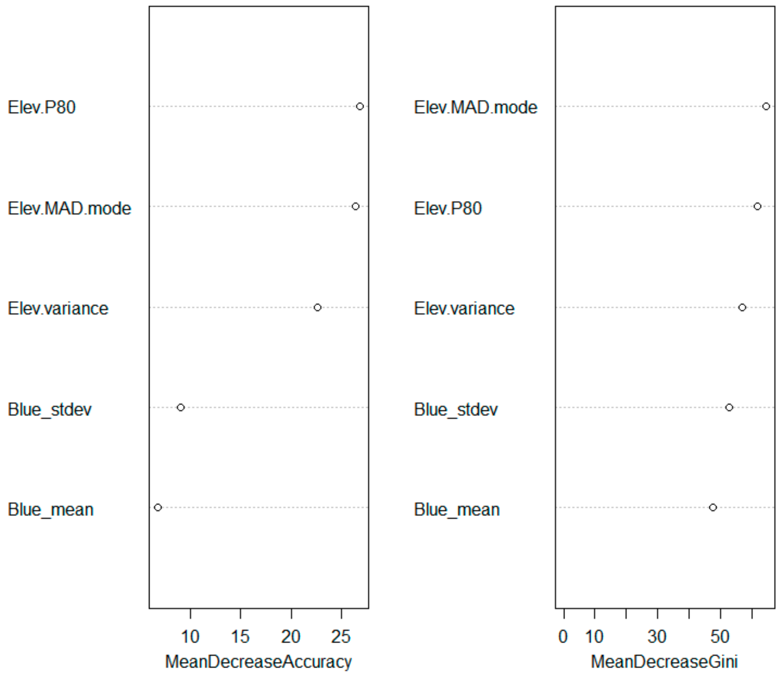

Figure 4. Importance of the predictors used in the classification for large-scale mapping of pinsapo fir forest typologies.

3.3. Pinsapo FIR Forest Types Map

Forest types were maps for the whole distribution area of *A. pinsapo* using the Random Forest classification algorithm. Table 5 shows the total and relative area occupied by each silvicultural type at the SN, SG and SB locations. The type with the largest surface area (3241 ha) was II1c (uneven-aged mixed stand of *A. pinsapo*). The second most represented type was the II0c uneven-aged pure stand of *A. pinsapo*) with 1075 ha. Types II1a and II0a (even-aged mixed and pure stands of A. pinsapo) had relatively large areas (858 and 552 ha, respectively), distributed mainly in SN. The type with the smallest presence was III1 (stands of other species with dominance of *A. pinsapo* in the lower stratum).

Table 5. Absolute and relative areas of the proposed silvicultural typologies and their distribution in the natural distribution area of *A. pinsapo* in Andalusia.

	SN		SG		SB	
	ha	**%**	**ha**	**%**	**ha**	**%**
II0a	539.11	12.85	-	-	-	-
II0b	56.64	1.35	-	-	-	-
II0c	758.95	18.09	265.24	42.60	38.85	25.54
II1a	696.44	16.60	16.99	2.73	0.14	0.09
II1b	4.19	0.01	0.17	0.03	-	-
II1c	2143.85	51.10	318.32	51.12	107.58	70.75
III1	-	-	21.92	3.52	5.51	3.62

Figure 5 shows the product resulting from applying the typological key to all the polygons with the presence of *A. pinsapo* in SG and SB.

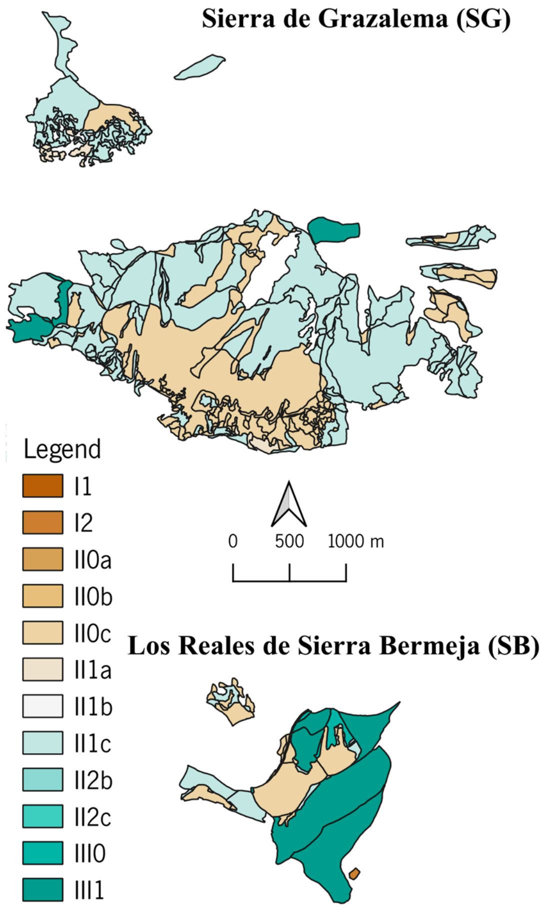

Figure 5. Application of the typological key to all the polygons with presence of *A. pinsapo* at SG and SB. See typology description in Table 1.

4. Discussion

In this study, a methodology for pinsapo fir forest typology is proposed as an example of applying multisource remote sensing data to classify, on a large spatial scale, fragmented and uneven Mediterranean forests with critical conservation concerns. First, we developed a forest typology classification based on traditional forest inventory metrics. Second, we used remote sensing data to spatialize the results on a large scale and improve the applicability of the classification. Overall, the models using LiDAR and multispectral information to predict forest typologies proved to be good indicators of forest typologies but showed varied outcomes across the different typologies.

4.1. Model Performance Analysis

In our study, we selected the Random Forest (RF) algorithm approach to predict forest typologies across the natural distribution area of the *Abies pinsapo* (≈4970 ha; Figure 1). RF has been implemented in a wide range of analyses with remote sensing data in forest research [47]. The ability to handle non-linearity and to quantify the importance of independent variables makes RF an effective algorithm [48]. However, comparative experiments were performed first using the Support Vector Machine (SVM) and Neural Network classifiers. These algorithms showed poorer results than RF in the accuracy tests for the validation dataset (Table 3), which is consistent with previous studies [49].

The classification accuracy of forest types based on multisource remote sensing data was moderate, and the overall accuracy was 62%. Among the classification results, uneven-aged stands exhibited the best results in terms of sensitivity, specificity and detection rate, while even-aged and two-aged stand types showed the lowest values. It can be noted that the algorithm had a high recognition for the forest types with a complex vertical stratification. On the other hand, inspection of the point cloud data revealed the presence of large trees and gaps with variable sizes in even-aged and two-aged stand types, which had a negative influence on the strength of the statistical relationship between ALS metrics and forest types [50].

These results are partially explained by the selected predictors. After application of the variable selection procedure (see Section 2.5.4), "Elev.P80", "Elev.MAD.mode" and "Elev.variance" from LiDAR data were the first features selected. These metrics described different aspects of forest structures: "Elev.P80" provides a measure of the higher elevation points in the dataset [51]; "Elev.MAD.mode" is associated with the homogeneity and variability of the vegetation structure [52]; and "Elev.variance" is related to the variability of tree heights within a forest stand [23]. The above-mentioned LiDAR metrics provide a comprehensive description of the vertical distribution of the forest. However, many of the LiDAR-derived metrics are strongly correlated and, therefore, the metrics selected in all studies represent complementary aspects of the 3D structure of forest stands. In our study, spectral information from aerial orthophotographs was also included, which confirms a complementary effect of the spectral signal and 3D features. "Blue_stdev" and "Blue_mean" were some of the selected variables. These variables described different aspects of forest composition: "Blue_stdev" provides a measure of variability in the blue band reflectance values, which can correlate with areas of high diversity, where different species and plant structures contribute to a diverse reflectance pattern. These results are similar to those obtained by the authors of [53], who found that the best individual image band for tree species discrimination was the blue band. This fact can explain the high detection rate (Table 4) of typologies that correspond to mixed stands (i.e., II1c and III1). Due to the differences in spectral characteristics and biological characteristics between *Abies pinsapo* and other mixed tree species, the inclusion of spectral data increases the accuracy of forest typology.

4.2. Pinsapo Fir Forest Types Classification

The forest typology for pinsapo fir developed here considered traditional forest attributes (i.e., dbh, tree density and species composition), making the typology an easy tool to be applied when forest inventory data are available and, at the same time, easy to be interpreted in the field. The forest type classification developed in this study was mostly consistent with previous typologies developed for the species [27,30]. Specifically, our typology increased the number of types compared with previous studies [30], in order to cover all environmental and structural differences found on the whole distribution area of the species in Andalusia. Across regions, we confirmed that the pinsapo fir forests of SN and SG are different in terms of structure and specific composition (Supplementary Material Tables S2 and S3), which coincides with the conclusions of other authors [10,27].

Stand delineation based on the proposed forest typology was used to develop specific forest management measures per each type (e.g., targeting thinning planning to decrease drought vulnerability or identify alternative plantation sites to promote recruitment) [54]. Therefore, the typology approach will be of great importance for the adaptation of pinsapo fir forests to the climatic risks expected for the Mediterranean basin [6]. In recent decades, the use of forest typologies has decreased, but this approach remains a reliable basis for silviculture [54]. The rapidly growing development of geo-spatial techniques is a great opportunity to improve the usability of forest typologies. The division of forests into management units implies the need to compute present forest state information on that scale. In this regard, forest typologies would benefit from using remote sensing data to infer structural characteristics of forest stands and thus project information at larger scales.

4.3. Pinsapo Fir Forest Map

Furthermore, the study demonstrated the potential of low-density ALS data combined with multispectral information from high-resolution orthophotos to predict the structural characteristics and composition of complex pinsapo fir forests. This finding is consistent with existing experiences on the use of low-density ALS data to estimate growing attributes in coniferous stands [17,55–57]. In view of the relevance of ALS methods in complex mix forests, it would be interesting to maximize the utility of low-density national LiDAR data. In fact, at this moment, several European countries offer national cover of open LiDAR data, and in some cases (e.g., Spain) temporal series (e.g., twice in Spain). However, the products obtained in the present work should be treated with caution. The results obtained in the validation statistics for some of the proposed types were moderate (see Table 4). Comparisons of the results obtained in this work with similar data from other studies are limited because of the novelty of the method. The precision of the definition of typologies in these cases is limited by two main reasons: (1) the lower number of observations of these typologies in the study area (Supplementary Material Table S1), due to the limited extension of pinsapo fir forests, and (2) the difficulty to discriminate between the stages of stand development using remotely sensed data.

4.4. Limitations and Future Recommendations

While there are good conceptual and empirical arguments supporting our conclusions, we acknowledge certain limitations and gaps in the data to effectively apply the proposed typology. First, four of the eleven proposed silvicultural types were not represented in the sampled plots and were therefore not reflected in the mapping. This does not mean that these silvicultural types are not correctly defined, but that no current representation exists. Second, due to the low density of ALS data, a major limitation of the proposed methodology is the uncertainty in discriminating between even-aged and two-aged stand types in areas where canopy tangency may exist, mainly in areas with a high fraction of canopy cover. Third, no forest inventory data are available for this study in SB. Although we strongly believe that pinsapo fir forests in SB have a similar structure to those in some areas of SN, such data could increase the accuracy of classification models for this region.

Thus, five important improvements should be addressed in future versions of the work: (1) incorporate further datasets for other distribution areas of *Abies pinsapo* (SB); (2) implement sample plots for the forest types that have not been represented in the present work; (3) increase the number of sampled plots of each forest type to increase the performance of the classification models; (4) use high-density LiDAR point clouds; (5) employ height- and intensity-based metrics derived from LiDAR data. In addition to the combination of multispectral and LiDAR data, future work may explore the use of multitemporal data available from middle-resolution imagery such as Landsat or Sentinel-2. Finally, as new modeling approaches and datasets are developed, there will be a need to re-analyze the existing data, with greater temporal and spatial resolutions.

5. Conclusions

We developed a novel methodology to map forest typologies across large scales using both ALS and multispectral information. The study case of pinsapo fir forests provided a relevant forest typology map at the stand scale suitable for operational forest management and for landscape management. *Abies pinsapo* Boiss. grow in forest formations structurally grouped in well-defined classes, fundamentally separated by the stages of stand development and composition criteria. Forest typology enables reflecting processes of forest vegetation dynamics on maps, producing excellent results in terms of systematizing. Since the methods proposed are based on freely available remote sensing data and freely accessible software, this methodology is transferable to other forest typologies and different spatial scales.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/rs16173182/s1, Description of LiDAR metrics; Table S1: Number of plots of each silvicultural type found in the sampled plots (n = 694); Table S2: Main structural characteristics of the seven types of pinsapo fir forests found in the sampled plots; Table S3: Importance values (%) of trees (dbh > 5 cm) found in sampled plots (n = 694) at pinsapo fir forests in SN and SG.

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