Identifying Forest Structural Types along an Aridity Gradient in Peninsular Spain: Integrating Low-Density LiDAR, Forest Inventory, and Aridity Index

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INTRODUCTION

The **characterization of forest structure** across **wide spatial scales** is essential for **forest monitoring and management**. Using different sources might help to better characterize forest structure at continuous scale.

LiDAR data have proven useful for **cost-effectively** estimating **forest structural attributes**.

Forest inventories are the largest sources of information of **forest states** at the national level.

Improving knowledge and characterizing **forest structure variations** along **large areas** remains a **priority** for **research, monitoring**, and land **management** (e.g., Torresan et al., 2016; Neuville et al., 2021).

OBJECTIVES

(i) to identify **typologies of forest structures** based on stand level NFI measurements and climatic variables via an unsupervised cluster analysis.

(ii) to **classify forest structure from LiDAR** metrics using a Random Forest modeling approach.

(iii) to **map regional patterns of forest structure** across a wide aridity gradient along peninsular Spain from low-density PNOA LiDAR data.

MATERIALS & METHODS

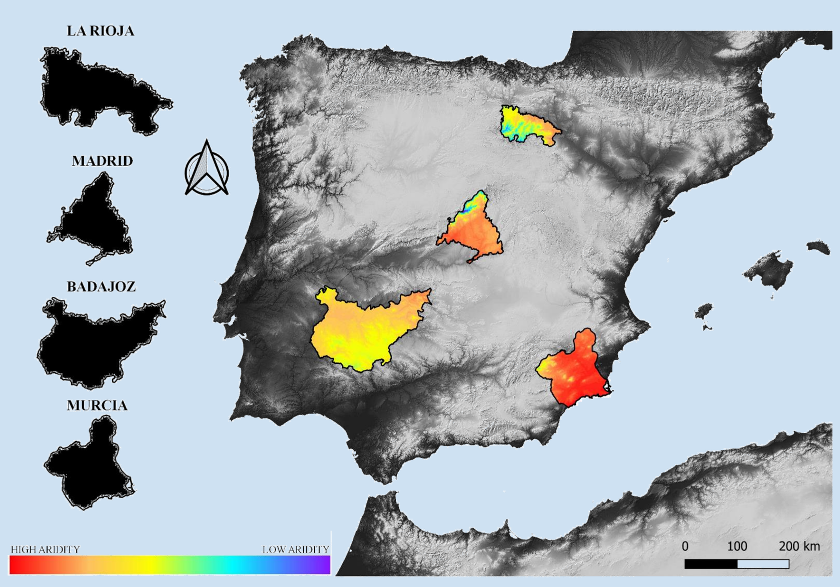

Fig. 1: Martonne aridity gradient and the location of the studied provinces in Spain.

We used a **large climatic gradient** (see Fig. 1, Martonne, 1926).

We used the **4th Spanish National Forest Inventory** (SNFI) to extract **six structural variables** to **define forest structure**, and **k-medoids clustering** algorithm to determine the optimal number of clusters (Fig. 2).

Using the **main tree species** in each structural cluster we defined the structural forest type (Fig 2).

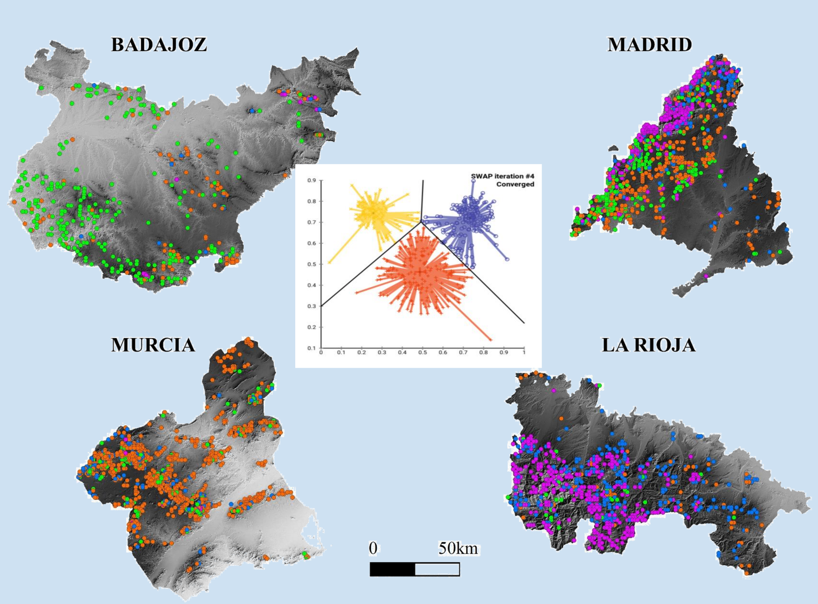

Fig. 2: Plot distribution of the 4th Spanish Forest Inventory used to define forest structural types per province and an example of k-medoids.

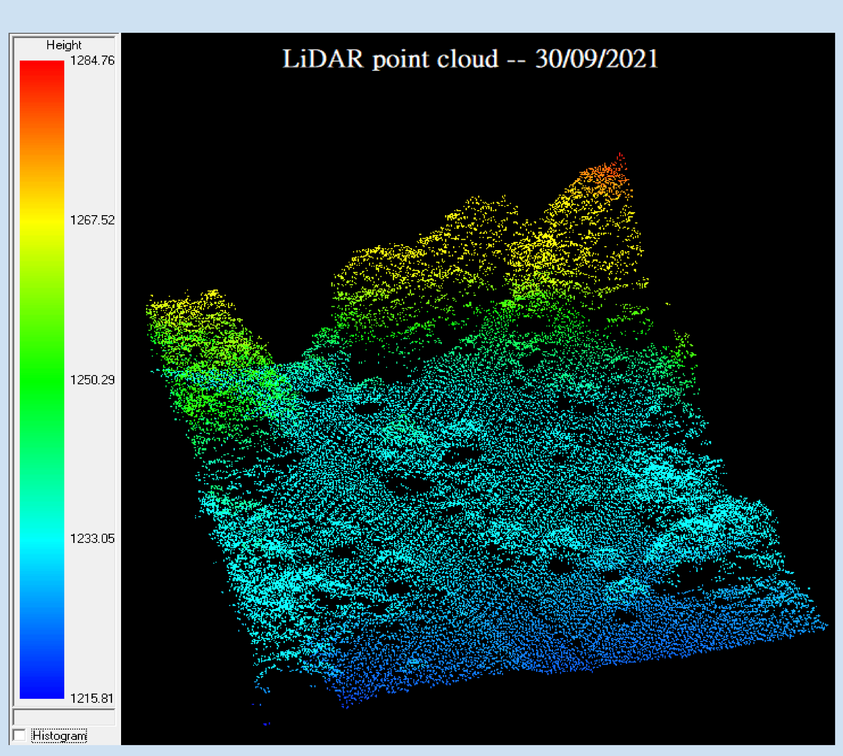

Fig. 3: PNOA-LiDAR data representation.

The defined structural types were characterised with **LiDAR variables.** With a **Random Forest model (RF)**, we spatialized the structural forest types in all the forests.

RESULTS

We identified four forest **structural types** for the **four provinces** studied, with significant differences in structural and climatic variables (Table 1).

Table 1: Mean and standard deviation of structural variables and the aridity index by each identified forest structural type based on the Spanish Forest Inventory.

Structural type	Basal area (m^2 ha^{-1})	Tree density (No. $trees^2$ ha^{-1})	Mean size (cm)	Mean tree height (m)	Aridity index
Sclerophyllous forests	7.91 (4.8)	314 (205.8)	21.3 (5.76)	7.99 (1.52)	18 (4.81)
Agrosilvopastoral and open woodland	9.59 (6.5)	151 (174.2)	41.2 (13.8)	8.07 (1.41)	21.1 (5.31)
Coppices and pines	22.1 (10.3)	1229 (564.5)	17.5 (5.23)	9.61 (1.81)	26 (8.13)
Mountain forests	29.1 (12.7)	654 (420.6)	30.5 (10.4)	13.8 (2.95)	36.6 (12.38)

The **RF model** had an overall accuracy of **60.63%** for the **training dataset** and **64.18%** for the **validation dataset**, thus showing **no overtraining** issues (Table 2).

Table 2: Contingency table for the training and the validation datasets.

CONTINGENCY TABLE (Training set: 70% of total observations)					
Predicted	Observed				User's accuracy (%)
	Sclerophyllous	Agrosilvopastoral and open woodland	Coppices and pines	Mountain forests	
Sclerophyllous	649	197	123	51	45,37
Agrosilvopastoral and open woodland	71	158	18	28	57,45
Coppices and pines	32	18	98	68	63,63
Mountain forests	33	40	84	270	63,23
Producer's accuracy (%)	82,68	38,26	30,34	64,75	Total accuracy (%)
					60,63
CONTINGENCY TABLE (Validation set: 30% of total observations)					
Predicted	Observed				User's accuracy (%)
	Sclerophyllous	Agrosilvopastoral and open woodland	Coppices and pines	Mountain forests	
Sclerophyllous	293	83	54	17	62,65
Agrosilvopastoral and open woodland	35	75	5	13	58,59
Coppices and pines	6	5	52	20	65,55
Mountain forests	11	16	33	114	65,52
Producer's accuracy (%)	84,93	41,90	36,11	69,51	Total accuracy (%)
					64,18

The **RF model** was used to **spatialize the results**, obtanining the **total extension** of each **forest structural type** and its **geographic distribution** (Fig. 4).

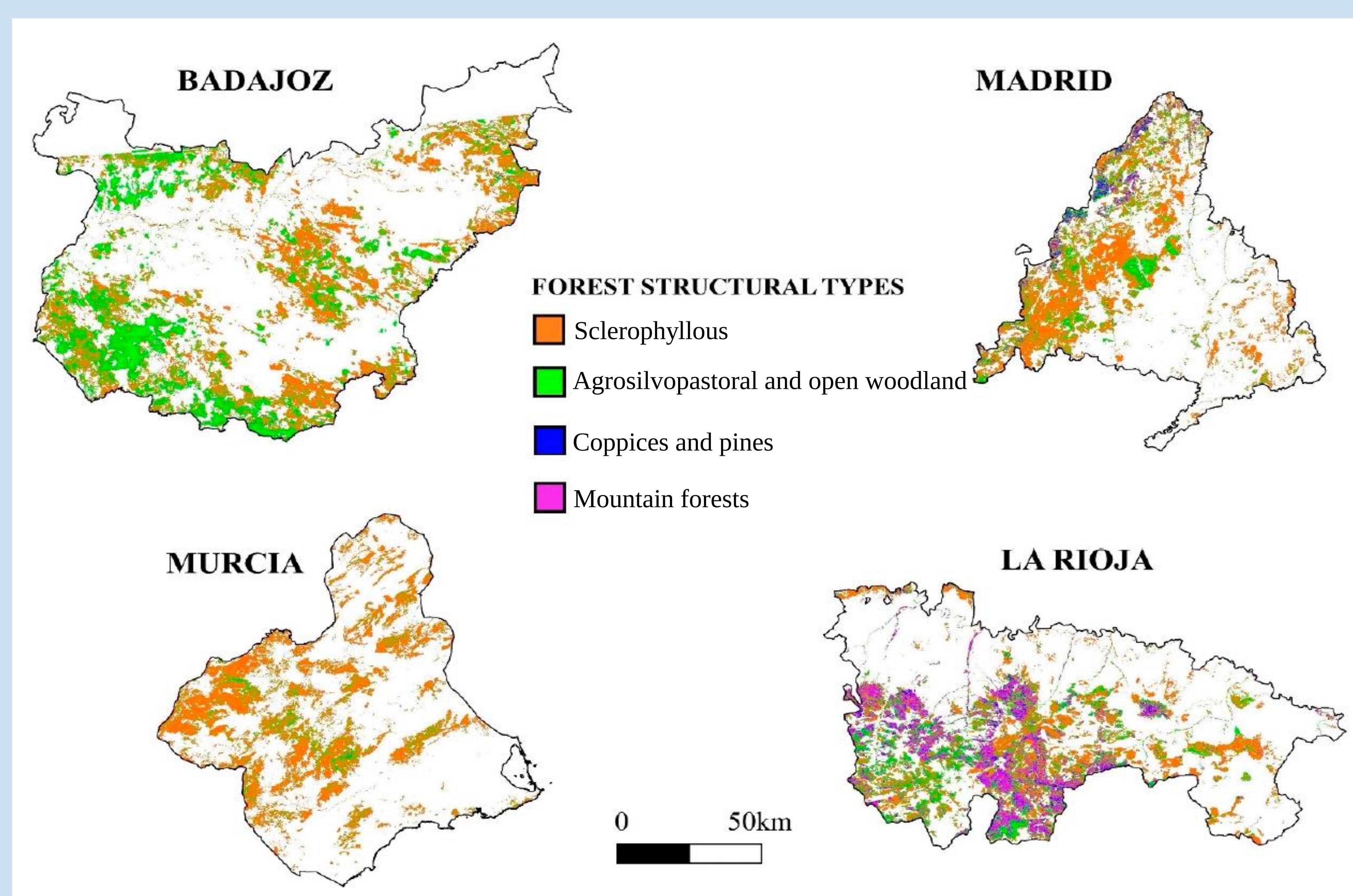

Fig. 4: Distribution of the predicted forest structural types using LiDAR data.

CONCLUSION

We identified **four** main **forest structural types** along the **aridity** gradient as determined by the main species, but with strong differences in structural characteristics and aridity (Table 1) .

The high **accuracy in RF (64,18%)** allowed for the **extrapolation of forest structural types** in areas without NFI data (Fig. 4). However, more detailed LiDAR data and planned temporal LiDAR and NFI campaigns could help to further improve the predictions and calculate temporal trends.

Our **methodology** can be **adapted to detect and analyze changes over space and time,** especially considering that the **PNOA includes multitemporal LiDAR coverage** for the whole of the **Spanish territory**.

REFERENCES

de Martonne (1926). *Géographes Français*. 3, 3–5.

Dodson et al (2012). *Canadian journal of forest research*. 42, 345–355.

Neuville et al (2021). *Remote Sensing*. 13, 352.

Torresan et al (2016). *Annals of Forest Research*. 59.

Restaino et al (2019). *Ecological Applications*. 29, e01902.

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