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BUILDING A NETWORK OF OVERMATURE FORESTS USING AIRBORNE LASER SCANNING AND LANDSCAPE GRAPHS

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ABSTRACT

Building a network of interconnected overmature forests is crucial to provide habitat and promote the dispersal of a multitude of species that depend on several forest structural maturity attributes such as very large living trees and deadwood. The use of Airborne Laser Scanning (ALS) to locate patches of overmature forests is still in progress. However, few studies have paid attention to the spatial distribution of overmature forests and its ecological consequences on landscape connectivity for species depending on forest structural overmaturity. In this study, we investigated the potential of ALS-derived maturity and connectivity indices to identify overmature forests that most contribute to connectivity and that could be integrated into a network of forest protected areas.

Index Terms— Airborne Laser Scanning, Forest overmaturity index, Ecological Indicators, Landscape connectivity, Biological conservation

1. INTRODUCTION

Overmature forests refer to the latest stages of forest dynamics, from the end of the growing stage to the collapse stage, that are often by-passed in forests managed for wood production. Overmature forests provide a large set of ecosystem services including biodiversity conservation because a multitude of species depends on the structural attributes of overmature forests such as saproxylic beetles and fungi, bryophytes, lichens and cavity-nesting birds [1-4].

The identification of overmature forest often relies on field protocols. The use of remote sensing data to identify overmature forests is in progress and has mainly focused on the detection of deadwood while composite forest maturity index was only recently evaluated [5-6]. The occurrence of overmature forests is nowadays not sufficient to provide resources for related species that have minimum area requirements and dispersal ability that is limited for most of the species depending on overmature forest [7-8].

Moreover, the location of forest protected areas is currently not based on their importance regarding their contribution to the landscape connectivity of the network of overmature forest stands.

In this study, we first characterized stand structural maturity by calculating a new index of maturity (*IMAT*) within a network of field plots in areas that were recently covered by ALS surveys in the Northern French Alps. The *IMAT* combines three maturity attributes that are the total basal area of very large living trees, the total basal area of large dead standing trees and the volume of large lying woody debris. We assumed that a combination of ALS metrics, that were useful to predict individual maturity attributes in other studies, may be operational to predict the *IMAT* and locate overmature forests.

Then, we accounted for the spatial configuration of overmature forests using landscape graphs. Landscape graphs are conceptual representations of a landscape that differentiate a matrix from suitable habitats connected by ecological corridors, depicted in our study by least-cost paths [9]. We built landscape graphs from the predictive *IMAT* map, associated with a land cover map, and species dispersal abilities. From the landscape graphs, we computed the index of Probability of Connectivity (*PC*) for each habitat patch. This index belongs to the family of indices that quantify the amount of reachable habitat for species [10]. The application of this framework illustrates how to build or maintain functional networks of interconnected overmature forests in a region either by locating new forest protected areas or prioritizing conservation and restoration actions.

2. MATERIAL AND METHODS

2.1. Study sites

The study area encompasses several mountain ranges of the French northern Pre-Alps (extent: 44.842895; 46.206168; 5.40024; 6.551510). These ranges are quite similar in terms of substratum (limestone), climate (temperate) and altitude (622 m to 1740 m). Forest stands are pure and mixed stands

dominated by European beech (*Fagus sylvatica*), Silver fir (*Abies alba*) and, in places, Norway spruce (*Picea abies*).

2.2 Index of forest maturity (*IMAT*)

We assessed forest structural maturity in 660 field plots with radius from 15 m to 20 m. Very large living trees (diameter at breast height (*dbh*) ≥ 77.5 cm), large dead standing trees (*dbh* ≥ 30 cm) and large lying woody debris (≥ 30 cm in basis diameter and ≥ 0.5 m in length) were recorded in each plots between 2006 and 2018. For each plot *i*, we calculated an index of maturity (*IMAT*) combining three attributes linked to structural maturity:

$$IMAT = \frac{1}{3} \left(\frac{GVLLT}{\eta_{.99}(GVLLT)} + \frac{GLDST}{\eta_{.99}(GLDST)} + \frac{VLWD}{\eta_{.99}(VLWD)} \right)$$

where *GVLLT* is the total basal area of very large living trees ($\text{m}^2.\text{ha}^{-1}$), *GLDST* is the total basal area of large dead standing trees ($\text{m}^2.\text{ha}^{-1}$) and *VLWD* is the volume of large lying woody debris ($\text{m}^3.\text{ha}^{-1}$). Values were capped to their respective 99% quantiles ($\eta_{.99}$) to ensure that extreme values do not carry too much weight in the further calculations.

2.3 ALS metrics

ALS metrics came from various surveys which flew between 2010 and 2019. ALS metrics were related to maximum heights, height distributions, intensity, stand density and canopy openness. They were computed for the normalized point clouds extracted from discs centered on the field plots and with a horizontal radius of 35 m, in order to include a buffer zone with a width that approximately corresponds to half of the average stand height. ALS metrics were either directly derived from the point cloud (heights and intensities of the vegetation returns) or calculated after detection of individual trees. In addition, elevation and slope were also integrated as predictors. Computations were performed using functions from R packages *lidaRtRee* and *lidR* [11].

2.4 Prediction of forest maturity (*IMAT*)

We related the *IMAT* calculated from field plots to the ALS metrics using a random forest regression algorithm. Random forests were grown on the basis of 1000 trees. The optimal value of the number of predictors sampled at each node of each tree was fixed to two according to a tuning procedure that aims to minimize the out-of-bag error estimate [12]. Model performance were evaluated with the Root Mean

Square Error of Prediction (*RMSEP/mean IMAT*) obtained from a 10 folds bootstrap cross-validation, and a Spearman correlation coefficient calculated between observed and predicted *IMAT*. To delineate overmature forests, we tested different thresholds on the *IMAT* and selected the one that maximizes the accuracy assessed from a comparison of predictions with an expert field validation campaign (68 validation plots). These analyses were performed using R software v.3.6.0 and the *randomForest* package v.4.6-14 [12]. Within our study area, we selected one range (652 km^2 , Fig. 1) to predict the *IMAT*, assess the link with stand composition and build landscape graphs.

2.5 Probability of connectivity (*PC*)

To assess connectivity, landscape graphs were constructed with *Graphab 2.4* software [13]. Following a field campaign, forest patches above 1 ha and *IMAT* > 0.25 were considered as potential habitat for species related to maturity attributes. A land use map was used to define the resistance to movement outside forests patches. In absence of biological data, we fixed resistance values to 1000 for artificial or mineral surfaces, 800 for water surfaces and 600 for open environments [14]. In forests, we use ALS-derived maturity to define resistance. We assume that resistance values were inversely proportional to the *IMAT* and ranged from 1 for habitats to 200 for the least mature forests [15]. Two landscape graphs were constructed considering maximum dispersal distances of 100 m and 1000 m, based on the current knowledge on taxa associated with overmature forests [8, 16].

Landscape connectivity was assessed using two indices (for each graph). First, the overall connectivity of the network was calculated with the Probability of Connectivity (*PC*) index. This index quantifies the amount of reachable habitat and was calculated as follows:

$$PC = \frac{\sum_{i=1}^n \sum_{j=1}^n a_i a_j p_{ij}^*}{A_L^2}$$

with a_i , a_j : capacity of habitat patches *i* and *j*; A_L : total landscape capacity *L*, p_{ij}^* : maximum probability of dispersal between habitat patches. Capacity combines habitat area and quality defined from the *IMAT*. The probabilities p_{ij} were evaluated for each pair of habitat patches by a negative exponential function that reflects the decrease in dispersal probability with distance. Second, a connectivity index for each habitat patch *k* was calculated as follows:

$$dPC_k = \frac{(PC_{-k} - PC)}{PC}$$

(A) Index of maturity (IMAT)

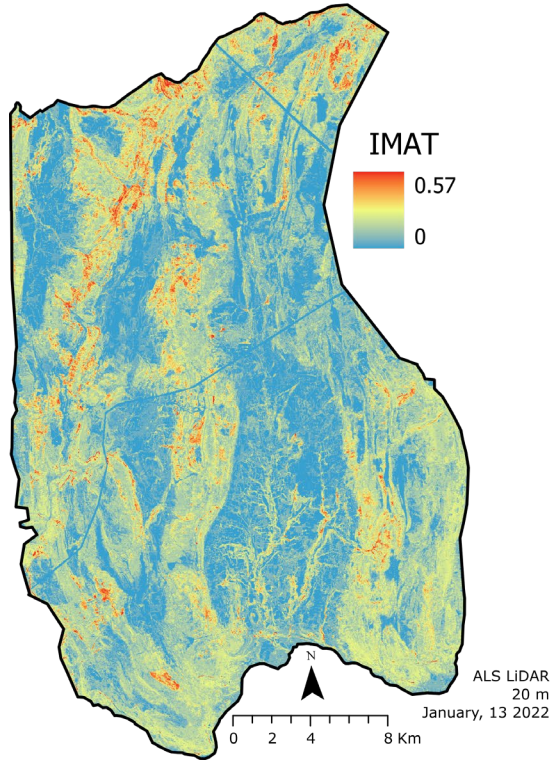
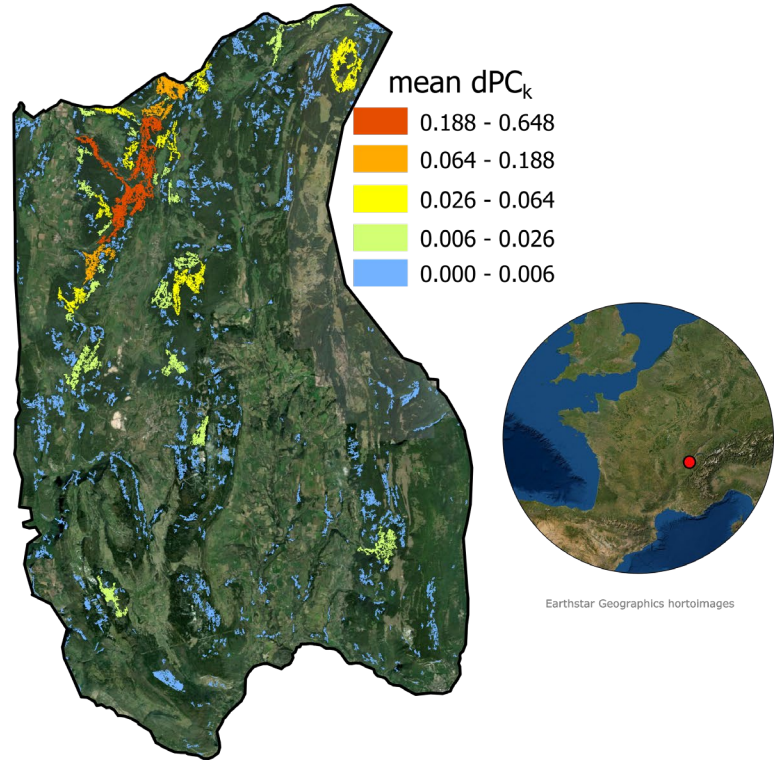
(B) Mean contribution to overall connectivity (mean dPC_k)

Fig. 1. Forest maturity (A) and landscape connectivity indices (B) that allow the identification of the overmature forest patches that contribute most to the overall connectivity of the network of overmature forest patches.

where dPC_k is the contribution of habitat k to overall connectivity as assessed by the PC index. The dPC_k index measures the reduction in overall PC connectivity when habitat patch k is removed from the network ($PC-k$). From both graphs (dispersal distance: 100 and 1000 m), the Pearson correlation coefficient and the mean dPC_k were calculated to summarize the contribution of each habitat to the connectivity of the two overmature forest networks.

3. RESULTS

Most of the field plots were not mature: $IMAT$ ranged from 0 to 1 but the average and median values were 0.14 and 0.07, respectively. This result underlines the need for landscape conservation planning.

$RMSEP$ was rather high: 76% of the mean $IMAT$ value or 114% when computed with validation data only. This came from a prediction bias where low $IMAT$ values tend to be slightly overestimated, while large values are underestimated by the model. The underestimation of the maturity of the most mature stands probably partly originates from the fact that from a certain diameter, growth in tree diameter is no longer accompanied by growth in height [17]. The rank correlation between observed and predicted values was high (Spearman correlation coefficient = 0.91). As a consequence, we accurately differentiate forests according to maturity degree, and even more so the

most and least mature forests by setting a threshold on the maturity index. The selected threshold ($IMAT = 0.25$) lead to an accuracy of 88%. This threshold implies that overmature forests generally include several maturity attributes and provide habitat for different species.

The most mature forests were mainly found in the northwestern part of the study area, within large and fairly continuous areas (Fig. 1A). This can be explained by the presence of a valley where fertility is important. The geographic disparity in maturity index was related to stand composition. The most mature forests were mostly found in coniferous stands ($IMAT > 0.25$ for 30% of coniferous areas) more present in the northwest, while deciduous and mixed forest were often less mature (18% and 11%, respectively). The presence of more isolated overmature forests can be explained by specific local stand management rules (retention silviculture) or by the presence of high-altitude streams with steep slopes.

The network that has been detected is not intended to be permanent due to logging. To build a viable ecological network, the priority is to start to protect the most important overmature forests. The importance is very consistent between the two landscape graphs that consider different dispersal distances (Pearson correlation coefficient = 0.96). The mean contribution to landscape connectivity (mean dPC_k) can therefore be used as a support to locate the most important habitat patches (Fig. 1B). We evidence that the

priority is to create forest protected areas to the northwest in order to start building a network that supports landscape connectivity conservation. In this area, we recommend the protection of four habitat patches that have a contribution of more than 6% and up to 65% of the overall connectivity (Fig 1B).

4. CONCLUSION

The innovative modelling framework illustrated in this study binds remote sensing and ecological connectivity models allowing to build a functional network of overmature forests filling two gaps: (i) the detection of overmature forest that can provide habitat for related species and (ii) the evaluation of habitat contribution to the connectivity of the whole overmature forest network to define forest protected areas and priorities for conservation and restoration actions.

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