



Integrating remote sensing and ground-based inventories to ecologically validate old-growthness across Italian forests

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Abstract: Mature and Old-Growth-like Forests (MOGF) are critical for biodiversity conservation and climate regulation, yet they remain rare and fragmented across Europe. This study aims to ecologically validate a high-resolution (30 m) predictive map of MOGF probability across Italy by integrating it with independent ground-based data from the 2015 National Forest Inventory (INFC2015). Utilizing a multi-source approach, we analyzed 6993 inventory sampling plots across diverse forest types and environmental gradients. Statistical analysis confirmed that higher MOGF probabilities strongly correlate with indicators of advanced stand development, including older age classes (> 120 years), multilayered vertical structures, and high canopy cover (> 80%). MOGF probability is also significantly higher within strictly protected areas (e.g., National Park Zone A) and topographically remote sites characterized by high altitudes and steep slopes. Quantitative correlations also link MOGF probability to an increase in above-ground biomass and deadwood. While the study successfully validates the spatial patterns of forest maturity, limitations include the current lack of national-scale 3D LiDAR data for deadwood modeling and the lack of microhabitat indicators in the INFC2015. However, the anticipated inclusion of these metrics in future national frameworks will further refine the monitoring of these ecosystems.

Key words: forestry; machine learning; structural complexity; explainable artificial intelligence; Nature Restoration Law.

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1. INTRODUCTION

While the global forest carbon sink has been stable over three decades, regional and biome variations exist (Pan et al., 2024). Old-growth forests with complex structures are associated with advanced succession, long periods of undisturbed growth, and high biological diversity (Puettmann et al., 2009). They feature unique processes that lead to ancient trees (Gilhen-Baker et al., 2022; Lindenmayer & Laurance, 2017), where the largest trees, top 1% by diameter, hold nearly half the biomass (Lutz et al., 2018). Old-growth forests are also characterized by increased deadwood (Lombardi et al., 2012; Šenħofa et al., 2020), and other biodiversity-related features, such as rare and/or endangered saproxylic beetle species (Eionet, 2021; Parisi et al., 2016, 2022), and tree-related microhabitats (Kozák et al., 2018; Larrieu et al., 2018; McGee, 2018), compared to managed forests. These attributes vary based on biogeography, forest types, human disturbance, and site conditions (Martin et al., 2020; Pesklevits et al., 2011), including productivity levels. Moreover, old-growth forests regulate hydrology (Crampe et al., 2021) and buffer climate extremes (Dellasala et al., 2020; Solano et al., 2025). At the stand level, they store 30-50% more carbon than managed forests (Keith et al., 2024), possibly the highest among terrestrial ecosystems (Mayer et al., 2020), offering insights into long-term forest dynamics and carbon storage without human interference (Martin-Benito et al., 2021).

Nevertheless, European old-growth forests are rare, fragmented, and often unprotected, covering about 2% of the forest area (Barredo et al., 2021). Identifying and monitoring them is a key challenge due to the lack of a universal definition, which varies by context (Bruening et al., 2024; O'Brien et al., 2021). Here, the term “old-growthness” was explicitly

adopted in several studies (e.g., Badalamenti et al., 2025; Barbati et al., 2012; Borghi et al., 2023) to refer to the degree to which forest stands express structural variability commonly found in old-growth forests, acknowledging that stands may or may not have been impacted by humans. European policies, including EU guidelines and the Nature Restoration Law, emphasize scalable, transparent conservation efforts given the role old-growth forests play in reducing emissions, combating climate change, and preserving biodiversity (Fraser et al., 2023; Mikolaš et al., 2023).

In this context, several studies employed diverse approaches to defining “old-growthness”, reflecting the complexity of applying this concept in heavily human-influenced landscapes, such as Mediterranean areas. Overall, a predominant approach used structural definitions rather than age-based criteria (Oliver & Larson, 1996), recognizing that Mediterranean forests rarely exhibit the complete absence of human impact associated with primary forests in other regions. Although the tree diameter at breast height can correlate with age (Pretzsch et al., 2020), direct age estimation across extensive forest areas requires labor-intensive methods, limiting practicality over large landscapes (Spracklen & Spracklen, 2019). Furthermore, the correlation between diameter and age often weakens in old-growth forests. Among canopy trees, diameter is an unreliable predictor of age; in fact, the oldest trees are rarely the largest (Piovesan et al., 2026; Piovesan & Biondi, 2021). On the other hand, structural definitions focused on specific measurable attributes such as mean tree diameter, standard deviation of tree diameter, and stand density of large trees with diameter larger than a certain threshold (Blasi et al., 2010a; Borghi et al., 2023). Another emphasized multi-sized diameter distribution, small-scale gap dynamics, tree height heterogeneity, high living volume

and basal area, and a ratio of dead to living wood not lower than 10% (Hahn & Christensen, 2005; Wirth et al., 2009a; Wirth et al., 2009b).

In this context, National Forest Inventories (NFI) provide robust forest data mainly through in situ measurements (Breidenbach et al., 2021; Tomppo et al., 2010), but ground data alone face limitations due to high costs, standardization needs, infrequent updates, and limited data access (Alberdi et al., 2016; Borghi et al., 2023; Gschwantner et al., 2019). On the other hand, advances in remote sensing and cloud computing (Gorelick et al., 2017) have further improved large-scale forest assessments (Wulder et al., 2016). Here, this research aims to demonstrate how structural complexity and old-growthness are distributed across different forest types and management levels at a national scale. This study is built upon the mapping framework developed by Borghi et al. (*submitted*), which utilized remote sensing, machine learning and Explainable Artificial Intelligence algorithms (Renflet et al., 2024) to map the Italy's Mature and Old-Growth-like Forests (MOGF) probability with 30 m resolution. The aim of this study is to provide an ecological validation of these results by linking remote sensing-based predictions with independent field measurements from the latest Italian National Forest Inventory (INFC). This integration is crucial for a multi-source monitoring approach; while remote sensing provides expansive spatial coverage, it often lacks the resolution to capture specific ground-level structural attributes - such as deadwood dynamics - which are fundamental indicators of old-growth status. By bridging these two scales, we tested whether the MOGF high-probability areas identified via remote-sensing and machine learning analysis truly exhibit the structural complexity recorded on the ground.

2. MATERIAL AND METHODS

2.1 Study area

The study took place in Italy (Figure 1), a country with diverse climate conditions due to its maritime influence and complex terrain shaped by the two main mountainous chains. Italy's climate is entirely Mediterranean, with colder, temperate zones in the north and sub-tropical areas along the southern coast and in lowland regions (Pinna, 1978). This environmental diversity supports a wide variety of forest ecosystems, which make up over a third of Italy's land area (De Laurentis & Piovesan, 2023; Mattioli et al., 2025). The 2015 National Forest Inventory (INFC2015) shows that Italian forests mainly consist of oaks (*Quercus* spp.) and European beech (*Fagus sylvatica* L.). In contrast, conifers such as Norway spruce (*Picea abies* [L.] H. Karst.) and various pines (*Pinus sylvestris* L., *P. nigra* J.F. Arnold, *P. pinea* L., *P. pinaster* Aiton) are predominantly found in coastal and northern areas, also in the form of plantations (De Laurentis et al., 2021).

2.2 Mature and Old-Growth-like Forest (MOGF) probability map

The modeling of forest structural maturity in this study is based on the framework established by Borghi et al. (*submitted*). This approach employs a Machine Learning and Explainable Artificial Intelligence pipeline to identify MOGF conditions across the topographically complex Italian peninsula, spanning Mediterranean to temperate-alpine gradients. In brief, the framework uses a Random Forest classifier trained on 22,032 reference areas, including high-integrity MOGF sites identified through expert knowledge and regional databases (e.g., Burrascano et al., 2018; Sabatini et al., 2021). In addition, a suite of high-resolution predictors was integrated to capture structural complexity and ecosystem function. Central to this was a Can-



Figure 1 - National distribution of Phase 3 2015 Italian National Inventory plots (i.e., 6993) colored by forest category.

opy Height Model (CHM) based on GEDI and Sentinel-2 data (Lang et al., 2023), further refined by deriving canopy height residuals using Big Additive Models (Wood, 2017). This normalization step effectively decoupled vegetation height from environmental constraints such as elevation, aspect, and latitude, highlighting stands with exceptional development relative to their site potential. Furthermore,

horizontal heterogeneity and productivity were characterized using the Rumble Index - derived from high-resolution 1-m CHMs (Tolan et al., 2024) - alongside national-scale maps of Growing Stock Volume, Carbon Stock and Current Annual Increment GEDI and Sentinel-2 data (Lang et al., 2023), further refined by deriving canopy height residuals using Big Additive Models (Wood, 2017).

2.3 *The Italian National Forest Inventory*

The Italian National Forest Inventory (NFI) has undergone a significant evolution across four distinct cycles, transitioning from a static periodic survey to a modern, dynamic annual monitoring system. The first National Forest Inventory (IFN85), conducted between 1983 and 1987, employed a simple 3-km systematic grid and single-phase sampling to provide the first nationwide estimates of forest cover. This was followed by the second (INFC2005) and third (INFC2015) inventories, which adopted Tessellation Stratified Sampling to improve statistical precision and integrated international carbon-pool monitoring protocols to assess aboveground biomass, deadwood, litter, and soil (Gasparini et al., 2022). Recently, the Italian NFI has been redesigned into a two-phase system with rotating panels, surveying the country's forest over five years to provide near-real-time data. The simplified sampling design enhances feasibility and efficiency, while maintaining consistency with past inventories for long-term comparability (D'Amico et al., 2025). However, data from this new system are currently being processed and are expected to be released in the coming years. Consequently, this study is based on the most recent available periodic inventory (i.e., INFC2015), ensuring consistency in characterizing forest structural maturity across Italy.

2.4 *Spatial and statistical analysis*

The methodology for analyzing the distribution of MOGF probability within the Italian National Forest Inventory (INFC 2015) framework is based on the spatial analysis of predicted MOGF probability values from Borghi et al. (*submitted*) onto 6993 sampling points of the INFC 2015 Phase 3 inventory (Figure 1). For each inventory point, MOGF probability values

were extracted from the high-resolution raster model using a point-in-polygon spatial join procedure. Based on the data available for each INFC2015 sample point - with a minimum of 10 plots per class - we focused on 24 INFC Phase 2 and 3 qualitative variables, grouped in five groups, namely (i) forest structure and origin; (ii) protection status; (iii) forest management and disturbance regime; (iv) site conditions, and (v) plot-level variables. Additionally, we calculated the correlation between the MOGF probability and the Phase 3 quantitative plot-level variables. Finally, statistical indicators, including the mean, median, and standard deviation, were calculated for each of the 24 qualitative variables to characterize the MOGF probability across varying structural and environmental gradients. Before performing the comparative analysis, the assumptions for parametric tests were assessed through the Shapiro-Wilk test (Shapiro et al., 1968) of the MOGF probability values, which strongly rejected the null hypothesis of normality. Consequently, the nonparametric Kruskal-Wallis H-test (Vargha & Delaney, 1998) was used to identify significant differences in MOGF distributions across categorical variables. For variables where the Kruskal-Wallis test indicated significant differences (i.e., $p < 0.05$), a Dunn post-hoc test for multiple comparisons (Dunn, 1961) was performed. The results of these pairwise comparisons were summarized using a Compact Letter Display (Gramm et al., 2007), where groups sharing at least one common letter are not significantly different from each other, while groups that do not share any letters represent statistically distinct MOGF probability distributions. All analyses were performed in R version 4.5.2 (R Core Team, 2026).

3. RESULTS

First, analysis of structural attributes and stand characteristics revealed distinct patterns in MOGF probability values across different forest categories, as shown in Figure 2. Regarding forest vertical structure, the Kruskal-Wallis test indicated significant differences among classes ($H = 128.86$, $p < 0.001$), with one-layer stands exhibiting a higher mean MOGF index (0.189 ± 0.230 , group “a”) than two-layer stands (0.129 ± 0.179 ; group “c”). Stand age demonstrated a significant positive relationship with MOGF high probability ($H = 197.88$, $p < 0.001$), with the highest mean values recorded in forests exceeding 120 years (0.294 ± 0.280 ; group “cd”) and those between 81 and 120 years (0.281 ± 0.285 ; group “c”), while the lowest scores were observed in the youngest 0-10 year age class (0.098 ± 0.168 ; group “ab”). Tree canopy cover also significantly influenced these results ($H = 37.34$, $p < 0.001$), as areas with canopy cover greater than 80% yielded the highest mean MOGF probability (0.207 ± 0.243 ; group “a”), whereas mean MOGF probability decreased progressively with lower canopy cover classes, reaching 0.135 ± 0.192 in the 11-20% cover category (group “ab”). Stand origin showed statistically significant ($H = 11.95$, $p = 0.003$) but minimal variation between natural (0.195 ± 0.237 ; group “a”) and semi-natural (0.195 ± 0.23 ; group “a”) origins, both of which maintained higher mean scores than planted stands (0.180 ± 0.234 ; group “b”). Finally, within development stages ($H = 243.28$, $p < 0.001$), mature and overaged high forests displayed the highest mean MOGF probability (0.280 ± 0.279 ; group “b”), contrasted by significantly lower values in young stands managed under special silvicultural systems (0.091 ± 0.110 ; group “a”) and young coppice forests (0.113 ± 0.170 ; group “a”).

Second, the analysis of administrative and legislative protection status identifies a strong relationship between formal conservation levels and the mean MOGF probability (Figure 3). Across all protection categories, areas under formal conservation consistently exhibit higher MOGF values compared to those outside such networks. The National Park designation serves as a primary driver within this group ($H = 74.60$, $p < 0.001$); forests within National Parks yield a mean MOGF of 0.269 ± 0.267 ($n = 522$), whereas areas outside these parks average 0.186 ± 0.230 ($n = 5001$). Within these parks, a clear hierarchical gradient emerges based on internal zoning ($H = 46.57$, $p < 0.001$): the highest mean MOGF probability is found in Zone A (Strict Nature Reserves) at 0.310 ± 0.284 , followed by Zone C (0.277 ± 0.266) and Zone B (0.231 ± 0.228), all exceeding the average for unclassified areas (0.189 ± 0.233). The statistical analysis revealed that National Parks across all protection categories belong to group “a”, with the highest median MOGF probability. Conversely, unprotected areas were categorized as group “b”, highlighting a significant statistical reduction in MOGF probability relative to protected areas sites. Regional and international protection frameworks show similar trends. Forests within Regional Nature Parks display a mean MOGF of 0.233 ± 0.236 compared to 0.190 ± 0.235 in unprotected counterparts ($H = 33.23$, $p < 0.001$). The influence of the NATURA 2000 network is also evident ($H = 51.34$, $p < 0.001$), as sites within the network show a higher mean probability (0.223 ± 0.245) than those outside (0.184 ± 0.231). Specifically, the combined SCI and SPA designation reaches a peak mean of 0.239 ± 0.245 ($H = 57.65$, $p < 0.001$). Similarly to National Parks, the protection level of NATURA 2000 sites showed statistically significant differences compared to non-classified areas (groups “a”



Figure 2 - Structure and origin, including the development stage, age class, structure (one or two-layers), and stand origin and tree canopy cover. The red triangle indicates the average for each category, while the number of sampled plots is reported. Plots are sorted and colored by the median MOGF value per group, from highest to lowest. Lowercase green letters show Dunn post-hoc results; categories sharing a letter are not significantly different, while those with different letters are statistically distinct.

and “b”). On the other hand, Regional Nature Reserves show a lower mean MOGF (0.159 ± 0.188) than external areas (0.194 ± 0.236), representing the only protection category in which the mean probability does not exceed the unprotected baseline and fails to show a

statistically significant effect on MOGF distribution ($H = 0.15$, $p = 0.695$; both group “a”).

Furthermore, the analysis of forest management and disturbance regimes reveals significant variations in the mean MOGF probability across diverse silvicultural and socio-economic

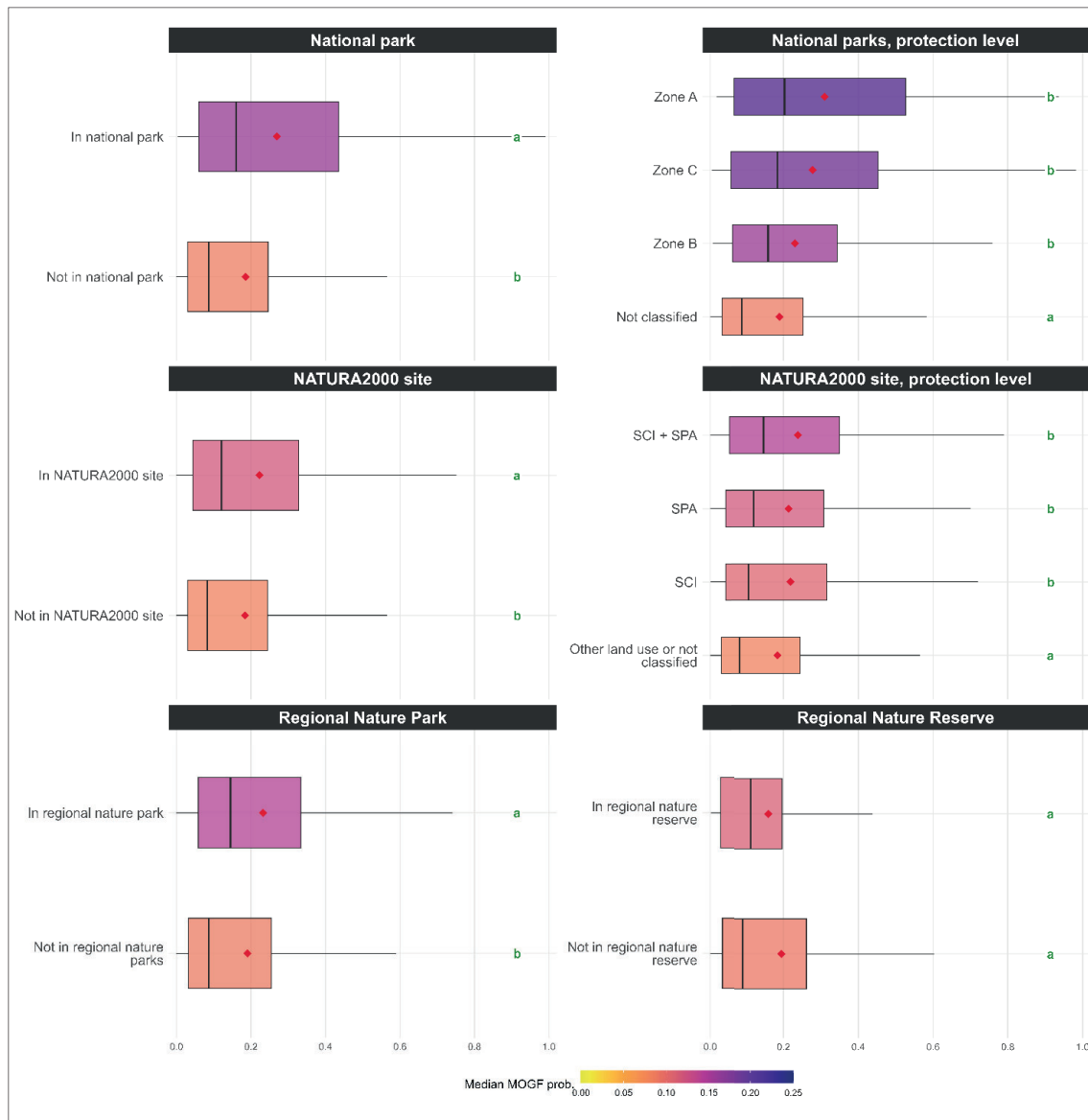


Figure 3 - Protection status, including the inclusion of the sampled plot within National parks and their protection level, Natura 2000 sites and their protection level, and Regional Nature Parks or Reserves. The red triangle indicates the average for each category, while the number of sampled plots is reported. Plots are sorted and colored by the median MOGF value per group, from highest to lowest. Lowercase green letters show Dunn post-hoc results; categories sharing a letter are not significantly different, while those with different letters are statistically distinct.

variables (Figure 4). The primary management objective emerges as a key driver of these patterns ($H = 33.62$, $p < 0.001$), with forests managed for naturalistic purposes exhibiting the highest MOGF (0.254 ± 0.289 , $n = 119$), fol-

lowed by those with protective indirect functions (0.230 ± 0.234 ; both group "a"). Conversely, stands managed for wood products (0.149 ± 0.205 ; group "b") and recreational purposes (0.127 ± 0.166) show markedly low-

er mean probabilities. Silvicultural systems also display a clear hierarchy ($H = 278.31$, $p < 0.001$) where uneven-aged or structured high forests recorded the highest MOGF probability (0.251 ± 0.264), closely followed by coppices in transition to high forest (0.242 ± 0.262). Both of these management types are classified in group “a” indicating they are statistically the most similar. In contrast, even-aged coppice systems (0.153 ± 0.202) and special silvicultural regimes (0.121 ± 0.155) maintain lower averages and are clustered in group “b”.

Further distinctions are observed in ownership and resource availability. Publicly owned forests exhibit a higher mean probability (0.234 ± 0.259) than privately owned stands (0.171 ± 0.217 ; $H = 97.96$, $p < 0.001$). Similarly, areas classified as not available for wood supply record a higher MOGF probability (0.214 ± 0.247) than those available for wood supply (0.192 ± 0.234 ; $H = 6.85$, $p = 0.009$). Regarding disturbance regimes, the cause of damage showed a significant relationship with MOGF probability ($H = 16.16$, $p = 0.006$), as forests affected by pests and diseases show the highest MOGF probability among damaging causes (0.222 ± 0.259 ; group “b”), whereas those subjected to browsing and grazing exhibit the lowest (0.074 ± 0.131 ; group “a”). Finally, an inverse relationship with damage severity is observed, with those with low damage exhibiting a higher MOGF probability (0.213 ± 0.242) than those with medium (0.169 ± 0.214) or severe damage (0.163 ± 0.213), although these differences were not statistically significant ($H = 2.58$, $p = 0.461$; all group “a”).

Next, the analysis of site conditions (Figure 5) reveals a clear correlation between topographical constraints - such as altitude and slope - and the MOGF probability, suggesting that environmental remoteness and terrain complexity favor forest maturity. Elevation is a primary driver within this group ($H = 660.74$,

$p < 0.001$); a robust altitudinal gradient is observed, where forests located above 2000 m asl exhibit the highest mean MOGF (0.291 ± 0.251 ; group “a”), followed by the 1501–2000 m asl class (0.276 ± 0.262 ; group “a”). Statistically significant differences were observed in plots located below 1000 m (group “c”). Here, probability decreases consistently with decreasing elevation, reaching its minimum in the 0–500 m asl range (0.101 ± 0.164 ; group “b”). A similar trend is evident for terrain morphology ($H = 112.84$, $p < 0.001$): steeper slopes ($> 80\%$) recorded a high mean MOGF of 0.243 ± 0.264 (group “a”), whereas areas with lower inclination (0–20%) show significantly lower values (0.154 ± 0.213 ; group “b”). Ground roughness ($H = 16.22$, $p < 0.001$) and terrain instability ($H = 27.87$, $p < 0.001$) further refine these patterns. Forests on “very rough” ground maintain a mean MOGF of 0.226 ± 0.256 , recording a larger mean MOGF probability than those on “smooth” terrain (0.188 ± 0.232). Statistically, “very rough” and “rough” terrains are clustered in group “a” while “smooth” terrain is assigned to group “b”. Furthermore, areas characterized by specific geomorphic disturbances, such as snowslides and avalanches, exhibit higher mean probabilities (0.214 ± 0.215 ; group “a”) compared to terrains with no documented instability (0.195 ± 0.237) - though both are statistically categorized within group “a” - or those affected by water erosion (0.148 ± 0.197 ; group “b”). Environmental remoteness also contributes significantly ($H = 80.39$, $p < 0.001$), as forests located 1001–2000 m from the closest road show higher mean MOGF values (0.248 ± 0.259) than those within 500 m (0.165 ± 0.212). Finally, the Kruskal-Wallis test results ($H = 49.52$, $p < 0.001$) confirm that solar exposure significantly influences the MOGF probability on the INFC2015 plots, with the variance in aspect categories reflecting a gradient. Statistically, the



Figure 4 - Forest management and disturbance regime, including the availability of the plot for wood supply, the character of forest ownership, the designated management objective and silvicultural systems, and the causes and severity of damage. The red triangle indicates the average for each category, while the number of sampled plots is reported. Plots are sorted and colored by the median MOGF value per group, from highest to lowest. Lowercase green letters show Dunn post-hoc results; categories sharing a letter are not significantly different, while those with different letters are statistically distinct.

North-West and South-East aspects represent the upper tier of probability scale with nearly identical mean values ($0.211 \div 0.249$ and $0.211 \div 0.243$, respectively). This high-probability group is followed closely by South-West and

West aspects, all in group “b”, denoting they are statistically different from the “no exposure” class ($0.124 \div 0.180$; group “c”). The transition categories, like North and North-East, serve as intermediate zones (groups “ab” or “ac”).



Figure 5 - Site conditions, including the class of altitude, aspect and slope, terrain instability, ground roughness, and distance to the closest road. The red triangle indicates the average for each category, while the number of sampled plots is reported. Plots are sorted and colored by the median MOGF value per group, from highest to lowest. Lowercase green letters show Dunn post-hoc results; categories sharing a letter are not significantly different, while those with different letters are statistically distinct. A statistical summary of the MOGF probability values for each category, along with the Kruskal-Wallis H-test, is available in Supplementary Materials, Tables S1-2.

Finally, the strongest positive correlations with MOGF probability are associated with metrics of forest productivity and biomass accumulation (Figure 6). Overall, the most positively

correlated metrics are the dry weight of (i) stem and large branches of living trees ($r = 0.343$), (ii) of stumps of living trees ($r = 0.339$) and (iii) of total above-ground biomass of living trees,

per hectare ($r = 0.330$). Similarly, the current annual volume increment of living trees ($r = 0.208$) and the dry weight of small branches ($r = 0.254$) emerge as positively correlated with MOGF probability. Furthermore, the presence of coarse woody debris ($r = 0.137$) and standing deadwood ($r = 0.117$) were also positively correlated with MOGF probability. Conversely, MOGF probability exhibited the strongest negative correlations with early successional stages or disturbed environments, particularly with class 2 shrubs (i.e., height >130 cm and diameter $0-2.4$ cm) with dry weight and carbon stock per hectare, both with $r = -0.147$. Overall, all reported correlations were statistically significant ($p < 0.001$).

4. DISCUSSION

In Europe, only a limited number of countries have conducted comprehensive ground-based inventories of old-growth forests (Mikoláš et al., 2019; Veen et al., 2010). In most cases, available data are either restricted to a few well-studied forests (Mikusinski et al., 2018; Savoie et al., 2016; Svoboda et al., 2014; Zmihorski et al., 2018), specific taxa (Meyer et al., 2021; Vandekerckhove et al., 2022), or rely primarily on remote sensing approaches for mapping the distribution of potential primary forests, which are yet to be confirmed (Hirschmugl et al., 2023; Sabatini et al., 2018; Schulze et al., 2019). In this context, our study provides an ecologically-based validation of the national-scale distribution of Mature and Old-Growth-like Forests (MOGF) probability across Italy proposed in Borghi et al. (*submitted*), using the ground-based observations from the last National Forest Inventory (INFC2015). Rather than representing a simple map validation, this approach enables a cross-scale ecological

interpretation of forest “old-growthness” as a continuous gradient of structural maturity, linking model outputs to measurable stand attributes. Specifically, we aim to compare national-scale satellite observations and detailed on-site structural measurements - especially those that remote sensing often misses, such as deadwood - to verify whether high-probability MOGF sites exhibit the biological and structural features of advanced forest successional stages. Overall, our results support the relationship between MOGF probability and Italian National Forest Inventory (INFC2015) attributes, providing robust external validation of the modelling framework (Figures 2-6). Indeed, higher MOGF probabilities are associated with indicators of advanced stand development, such as developmental stage classes (e.g., Figure 2) and tend to increase along the developmental gradient, with higher median values observed in the oldest age classes (Figure 2, 81–120 years; >120 years). These findings align with Borghi et al. (2023), who reported that high biodiversity and old-growth characteristics are observed in high forests, especially in uneven-aged ecosystems. At the same time, the inverse relationship between MOGF probability and dense shrub layers suggests that early successional or post-disturbance conditions are less likely to exhibit characteristics of structural maturity. However, the variability observed within age classes - including both low and high MOGF probabilities in intermediate stages - indicates that structural maturity cannot be explained by stand age alone. Rather, it reflects the cumulative effects of long-term continuity, disturbance history, and structural reorganization (Piovesan & Biondi, 2021). In this perspective, MOGF probability values increase with descriptors capturing vertical structural complexity, such as the shrub and tree canopy cover (Figure 2), indicating a clear association with advanced structural

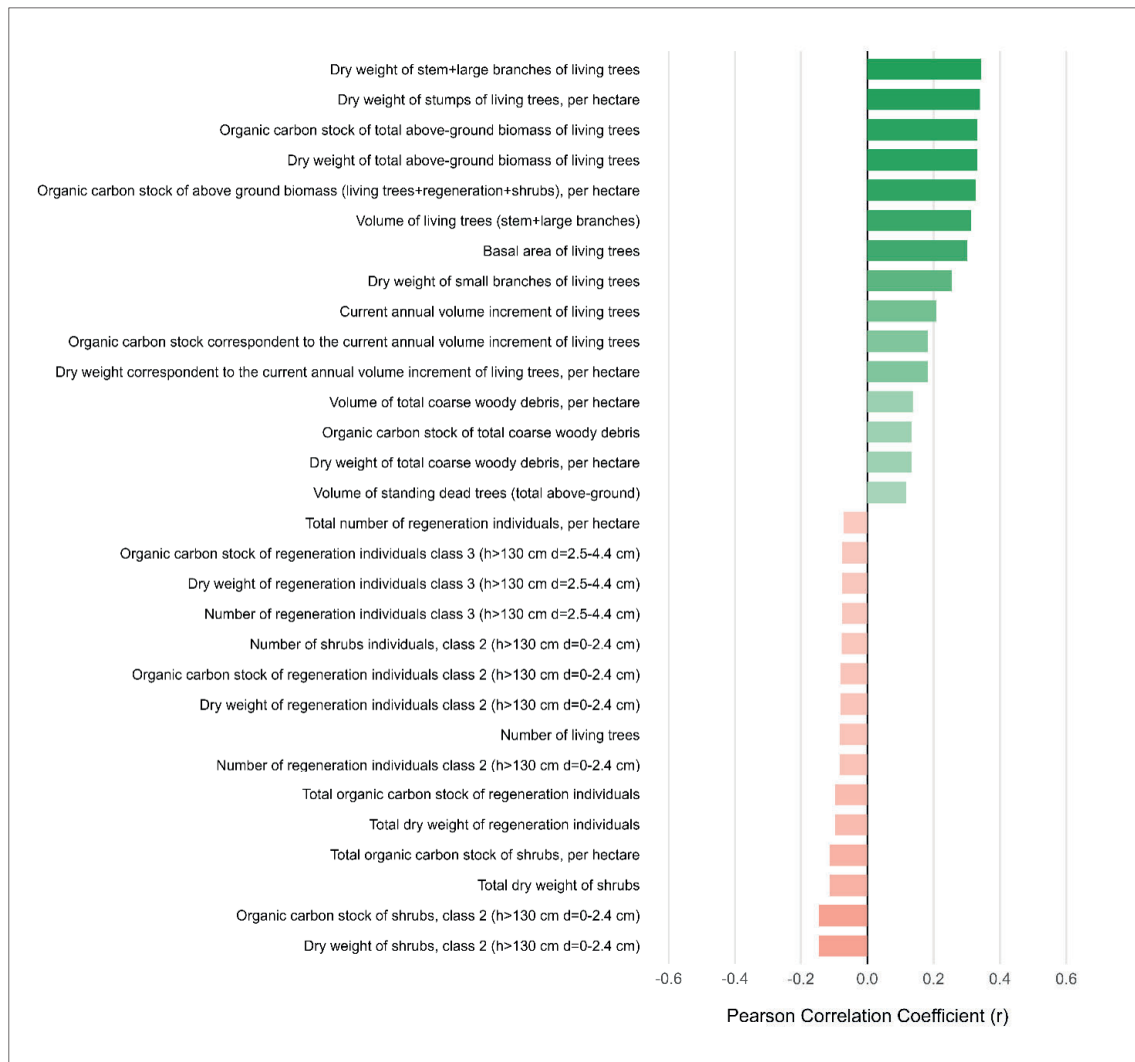


Figure 6 - Correlation between INFC2015 Phase 3 variables and MOGF probability (Borgghi et al., *submitted*). For visual purposes, only the 15 most and least correlated variables are shown.

development. Similarly, the positive relationship between deadwood accumulation and the MOGF probability (Figure 6, “Volume of total coarse woody debris, per hectare”) further supports its ecological relevance (Blasi et al., 2010b), reflecting increasing structural complexity and successional maturity. On the other hand, higher MOGF values are consistently associated with reduced or absent productive use (Figure 4) and with stricter protection regimes (Figure 3), although substantial overlap

among categories indicates that the model does not simply reproduce existing conservation designations. Instead, it identifies structurally mature forest conditions both inside and outside protected areas, highlighting a partial mismatch between protection status and ecological maturity. This finding suggests that significant reservoirs of structural complexity may remain unprotected, reinforcing the need for conservation strategies that extend beyond designated areas and incorporate structural in-

dicators into landscape-level planning (Chiti & Piovesan, 2025). Nevertheless, protection status remains a strong driver of MOGF probability. Forests located within National Parks or Natura 2000 sites show significantly higher values (Figure 3), with the highest probabilities observed in strictly protected zones (e.g., Zone A of National Parks). Conversely, the absence of formal protection emerges as a limiting factor for the development and persistence of old-growth characteristics in the Italian forest landscape. Our results are thus in line with Capotorti et al. (2012), who found that a long-term protection regime is especially effective for conserving aging forest communities, threatened vascular plants, and addressing contrasting threats caused by changes in human activities. Indeed, especially in the lowland Continental and Mediterranean areas, forest dynamics are often characterized by human-driven, short, and intense disturbance cycles that prevent forests from advancing to more mature stages (Figures 2 and 4).

Regarding site conditions, the high correlation between MOGF and topographic constraints - such as high altitude and steep slope - supports the hypothesis that forest maturity in Italy is a legacy of marginality. In these contexts, physical constraints have historically rendered timber extraction economically unfeasible (Marchetti & Blasi, 2010; Newbold et al., 2015). This pattern is consistent with several Italian studies (Agnoletti et al., 2022; Barbati et al., 2012; Motta, 2002), which identify old-growth forests primarily in mountainous and impervious areas, as recently reported in an Italian-scale review by Motta et al. (2022). Similarly, the observed influence of sun exposure further suggests that microclimatic conditions - especially on South-facing forests - may perhaps influence the availability of habitat niches (Hagge et al., 2024; Seibold et al., 2015). For instance, while biodiversity metrics

were not directly measured within the INFC plots, our findings on MOGF probability align with ecological studies in similar Italian contexts (Parisi et al., 2023). Taken together, the independent INFC2015 data support the view of old-growthness as an emergent property of forest ecosystems shaped by site-specific environmental constraints, disturbance histories, and land-use legacies. The convergence between model outputs and independent inventory data helps delineate the ecological space occupied by structurally mature and old-growth forests at the national scale and supports the robustness and ecological interpretability of the probabilistic framework.

5. CONCLUSIONS

It became clear that to improve the protection of old-growth forests across Europe, efforts should focus on making NFI data available to assess old-growth forest variables at stand and landscape levels. This might help support national strategies across different regions and different biomes. The upcoming updates to national inventories, combined with advanced remote sensing technologies, present a transformative opportunity for MOGF research. A key advantage is the integration of ground-based biodiversity metrics, such as tree-related microhabitats, which will be included in Italy's next forest inventory cycle. Additionally, using LiDAR-derived metrics can enhance old-growth forest classification beyond traditional point density models. By effectively scaling these high-resolution structural metrics while maintaining horizontal heterogeneity, such as canopy gaps and height variation, future models can better represent gap-phase dynamics crucial for natural forest development. Ultimately, combining long-term satellite-based temporal analy-

sis with precise in-situ assessment will create a comprehensive monitoring system to guide decision-making and promote the long-term conservation of these biodiversity hotspots.

Nevertheless, the current study highlights important limitations due to the limited thematic detail of currently available national datasets, while also pointing to valuable opportunities for future research. A key challenge is the lack of specific biodiversity indicators, especially tree-related microhabitats, within the INFC2015 framework. This absence prevented a direct comparison between ground-based biodiversity measures and the predictive map produced by Borghi et al. (*submitted*). Nevertheless, this gap is anticipated to be addressed soon, as these indicators are planned to be incorporated into the next Italian national forest inventory cycle (D'Amico et al., 2025). Furthermore, the predictive power of the current map is limited by the exclusion of deadwood as a structural variable. While deadwood is a fundamental component of biodiversity and a well-known indicator of forest old-growth status (Borghi et al., 2023; Dufour-Pelletier et al., 2020; Šenhofa et al., 2020), its integration as a spatial predictor is hindered by the difficulties of remote-sensing based assessment (e.g., Marchi et al., 2018), especially lying, smaller pieces and/or in conditions of dense canopies (Amiri et al., 2019; Diätenberger et al., 2025). The acquisition of such high-resolution structural data would therefore be essential to better characterize both vertical and horizontal forest complexity, ultimately enabling a more robust inclusion of necrotic biomass in future modeling efforts. A recent study (Adiningrat et al., 2025) further highlights the importance of LiDAR-derived structural and canopy metrics - such as canopy surface roughness (Rumple index), vertical layering diversity (vertical complexity index), and canopy openness (gap fraction) - for improving

the classification of old-growth forests, achieving higher accuracy than previous approaches that relied solely on height and point density metrics (de Assis Barros & Elkin, 2021). However, as reported by the authors, the approach is limited to temperate forests under conditions similar to those of the case study, thereby restricting its applicability across broader biogeographical contexts (Tíscar & Lucas-Borja, 2016). Moreover, upscaling to larger areas risks losing horizontal heterogeneity, such as tree height variability and canopy gaps, which can reduce the accuracy of old-growth forest identification (Markham et al., 2023). In particular, gap-phase dynamics are important drivers of structural development (Franklin et al., 2004). Furthermore, the study of gap dynamics in old-growth forests would provide a key reference for implementing management strategies that restore native biodiversity by imitating the structural and ecological features of old-growth conditions in managed or human-impacted forests (Seymour et al., 2002; Solano et al., 2021). Despite these limitations, combining in-situ measurements with satellite-based remote sensing and Earth observation data may provide complementary advantages. While field data offer detailed insights into forest attributes that are difficult to detect remotely, remote sensing enables broad-scale monitoring of forest dynamics, including forest disturbance. Besides, satellite data can validate interpolated field maps, while in-situ data can calibrate and validate Earth observation products or serve as input for modeling approaches (McRoberts et al., 2018). This complementary integration may also open opportunities for reconstruction of ecological, structural, and dynamic trends through temporal analyses (Martin et al., 2021a; Martin et al., 2021b). Such approaches can ultimately enhance decision-making processes, supporting more effective forest conservation, monitoring, and restoration planning.

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