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# Allometry, biomass, and productivity of deciduous oak forests in Xanthi, northern Greece

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In this work, the data collected for the preparation of the management plans prepared by the Xanthi Forestry Service were used to estimate the biomass allometry and productivity of the deciduous oak forests. For the purpose of our study, the diameter at breast height (DBH), distribution of trees above breast height, and the wood stock amounts were analyzed. To estimate the aboveground biomass, three biomass models were tested. The DBH distribution clearly indicated that the majority of the stands were young, thus having a high net productivity. This fact suggests that, in order to get a fair estimate of biomass, a biomass expansion factor (BEF), used to convert volume to mass, should have a value close to the upper limit of the factor's range, which is appropriate for young stands. The comparison of the three tested models proved that only one could be appropriate for use while the other two were completely unsuitable.

**Keywords:** Allometry, biomass, deciduous oak forests, productivity

Forest ecosystems are globally recognized for their critical role in terrestrial carbon dynamics, providing invaluable services to humankind and acting as significant carbon sinks (Bonan, 2008; Pan *et al*., 2011). Since the onset of the industrial revolution, drastic climate changes have been predominantly attributed to human activities that escalate greenhouse gas emissions, particularly carbon dioxide ($CO_2$), methane ($CH_4$), and nitrous oxide ($N_2O$). Among these, $CO_2$ is the primary contributor, with its atmospheric concentration having increased dramatically since pre-industrial times (Forster *et al*., 2007). According to the latest data from the National Oceanic and Atmospheric Administration (NOAA), $CO_2$ levels have reached unprecedented highs, crossing 421 parts per million (ppm), signaling an urgent need to understand and enhance carbon sequestration processes (NOAA, 2022).

Forests worldwide play a pivotal role in sequestering carbon, accounting for an estimated global carbon uptake of around 900 petagrams (Pg C), and sequestering about 1.1 teragrams (t C) annually (Sabatini *et al*., 2019). Photosynthesis enables plants to absorb atmospheric $CO_2$, releasing oxygen and incorporating carbon into their biomass and soil. This carbon allocation across various forest compartments, including above-ground and below-ground biomass, dead wood, litter, and soil organic matter, and the resulting carbon fluxes from leaf and fine root turnover, are essential to understanding ecosystem dynamics (Pan *et al*., 2011; IPCC, 2014). In European temperate forests, the total carbon storage is estimated to be approximately 110 t C/ha, with soil contributing up to 65 t C/ha, highlighting the importance of these carbon reservoirs (Brunner & Godbold, 2007).

In addition to natural processes, incremental growth in trees also suggests an increase in carbon storage. This is particularly evident in tree trunks, where their growing biomass is closely correlated with the sequestered carbon content (Stephenson *et al*., 2014). Accurate quantification of biomass—and, by extension, carbon reserves—requires both

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direct measurement techniques, such as harvesting trees for biomass calculation, soil coring for below-ground carbon content, and litter traps for detritus biomass (Rustad *et al*., 2001), as well as indirect methods involving allometric models that relate tree dimensions to dry biomass (Chave *et al*., 2014). Biomass expansion factors (BEFs) are also used in conjunction with these models to adjust for variations in biomass accumulation depending on tree size, age, and forest management practices (Penman *et al*., 2003).

Indirect methods, while less invasive and more practical than direct methods over large scales, depend heavily on the accuracy and applicability of the allometric models and BEFs used. These models are crucial for estimating the amount of carbon sequestered within a forest ecosystem, contributing to our understanding of global carbon budgets and informing climate change mitigation strategies. Ensuring that the allometric models are region-specific and representative of the true complexities of forest structures and species compositions is vital (Lehtonen *et al*., 2004; Gasparini *et al.*, 2015).

This research was part of the ForOaks Project, supported by the Green Fund, which aims to enhance the national greenhouse gas inventory in Greece by dynamically assessing $CO_2$ sequestration in deciduous oak forests and evergreen broadleaved forests. In this regard, this study was conducted to ascertain the optimal allometric model for determining the aboveground biomass of the deciduous oak forests located in the Regional Unit of Xanthi, northern Greece, which are under the jurisdiction of Xanthi Forest Service (XFS). By scrutinizing the established allometric models in conjunction with the data from the local forest management plans, our objectives were to refine the biomass estimates and elucidate the carbon dynamics within these temperate woodlands.

## Materials and methods

## Study area

The study was conducted in the Year 2023 in the oak-dominated deciduous forests located within the Xanthi regional unit of East Macedonia and Thrace, northern Greece (see Figure 1). The study area is situated between 41.0771312–41.4079084 N latitudes and between 24.6089329–25.2263813 E longitudes. The altitude of the terrain ranges from 50 m to 1827 m above the mean sea level. The study area exhibits Csa (Hot-summer humid continental) and Dfb (humid continental mild summer, wet all year) types of climate (Köppen-Geiger Explorer, nondated). The annual average temperature varies from 4.87 $^{o}$C to 14.57 $^{o}$C, and the annual average precipitation varies from 532 mm to 773 mm (WorldClim, nondated). Encompassing over an area of 34,791.92 ha, these forests constitute 55.30% of the region's forest cover, as outlined in the XFS' official management plans (XFS, 2023a, 2023b, 2023c, 2023d, 2023e, 2023f, & 2023g). The study area is characterized by a mosaic of tree species, reflecting a blend of broadleaf deciduous and evergreen vegetation. The area is mostly dominated by oak species such as *Quercus frainetto, Q. petraea*, *Q. pubescens*, and *Q. cerris* associated with beech (*Fagus sylvatica*) and other broadleaf species.

***Methods used***

Utilizing the high-resolution satellite imagery from the Google Earth Pro, we delineated the study area (indicated in red color in Figure 1). Nested within this domain were several forest complexes (each indicated in distinct color in Figure 2): Thermes-Satres (white), Kotili (blue), Oreo (black), Echinos (brown), Miki (purple), Gerakas-Xanthi-Kimmeria (green), and Drimos (orange). The red markers, in Figure 2, pinpoints the locations of the sample plots established for the measurement of tress for evaluation of biomass and allometric relationships.


**Figure 1: Screenshot of Google Earth Pro showing the forested areas under the jurisdiction of XFS, indicated in red color (Source: Google Earth, 2023).**

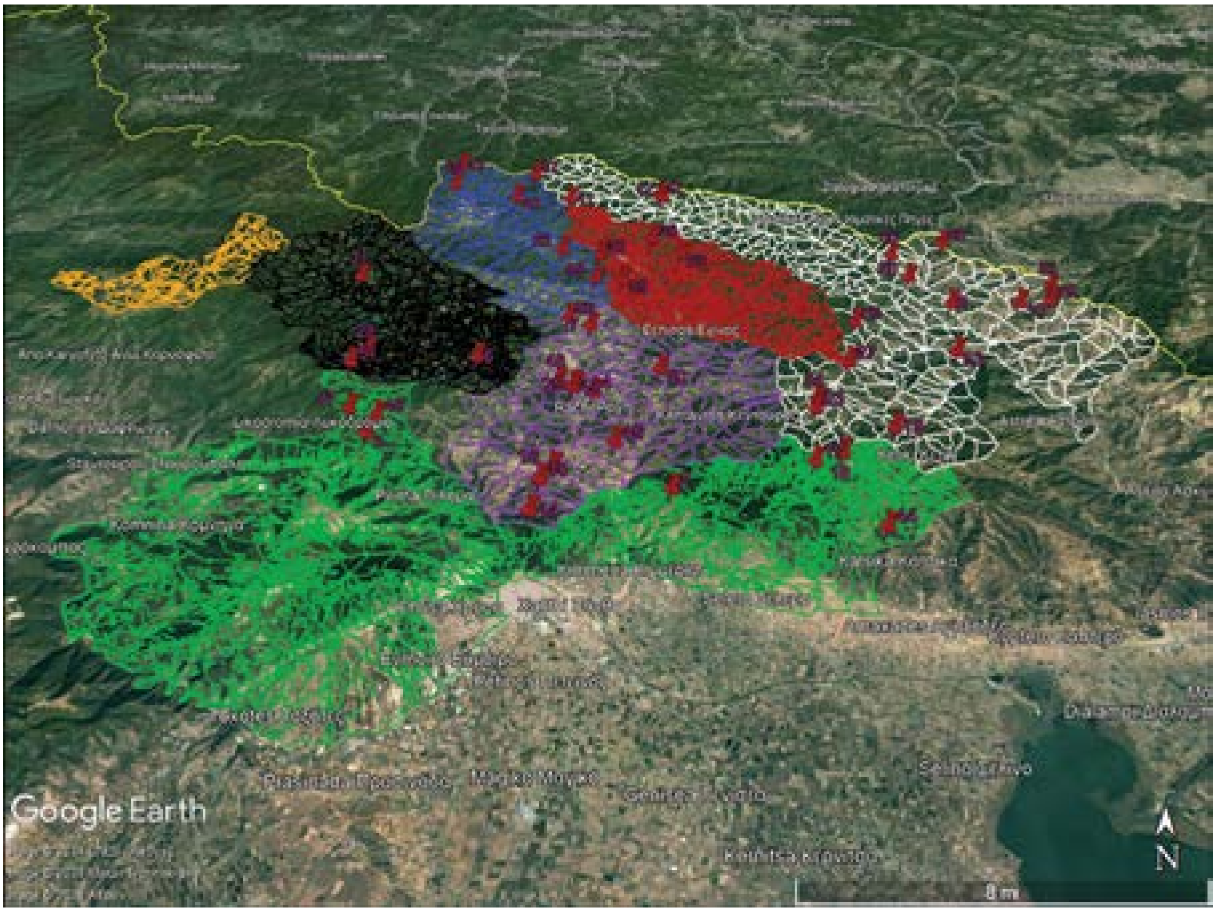


**Figure 2: Jurisdiction of XFS- showing the forest complexes (stand blocks) in distinct colors- Thermes-Satres (white), Kotili (blue), Oreo (black), Echinos (brown), Miki (purple), Gerakas-Xanthi-Kimmeria (green), and Drimos (orange); red pins correspond to sampling points.**

***Criteria for choosing biomass allometric models to test***

Selecting the right biomass allometric models is of paramount importance for the accurate assessment of forest biomass, especially when direct measurements are impractical or unfeasible. Following the structured methodology recommended by the Intergovernmental Panel on Climate Change (IPCC), we adopted a systematic, tiered approach to identify the models that provide the best fit for our study's specific requirements (Penman *et al*., 2003; IPCC, 2006).

The Tier 1 approach is considered the most fundamental level of the IPCC framework, where default models and conversion factors based on global averages are employed. Although Tier 1 models are readily accessible and broadly applicable, they are often too generalized. This can result in substantial discrepancies when applied to localized contexts, thus compromising precision and potentially introducing significant uncertainties in regional biomass estimations (Goetz & Dubayah, 2011; Henry *et al*., 2011).

Tier 2 builds upon the foundation of Tier 1 by introducing the enhanced accuracy based on the country-specific or regional allometric equations. These models, based on datasets gathered from biomes and ecological zones akin to those being studied, provide a moderate level of specificity without necessitating the comprehensive data inputs of more advanced tiers. By integrating localized growth patterns and species-specific attributes, Tier 2 models bridge the gap between the generalizations of global averages and the granular detail of localized field data, offering a sensible compromise for many research endeavors (Chave *et al*., 2014; McRoberts *et al*., 2012).

At the apex of the tiered system, Tier 3 epitomizes precision through the adoption of site-specific allometric equations. These models are developed from rigorous and extensive field research, tailored to the unique conditions of the study area. They consider localized climate, soil properties, and forest management practices, thereby affording scientists the capability to conduct finely tuned biomass estimations. While Tier 3 yields the highest degree of accuracy, its employment is contingent upon the availability of substantial field data, extensive research efforts, and often larger financial resources, which can limit its applicability, particularly in less-studied or -funded regions (Pilli *et al*., 2006).

In our research, we aligned with the Tier 2 protocol due to its viable blend of precision and data accessibility. The rationale for this choice were based on the following considerations:

1. Tier 1 models are insufficient for our study purpose because of their universal nature, not accounting for the heterogeneity inherent in the regional ecological settings. Their application could lead to misrepresentations of the actual biomass in our study area due to the absence of regional calibration (Sileshi, 2014).

2. Tier 2 offers an intermediate route, relying on a wealth of data that has been tailored to the Greek context, specifically addressing the characteristics of the oak species that dominate our study landscapes. The use of these models facilitates more reliable biomass estimations that harmonize better with the ecological nuances of the Mediterranean region.

3. Although Tier 3 represents the optimum in terms of model accuracy, it is not a feasible option given the limitations in our data collection capabilities and the extent of resources currently at our disposal. Engaging with Tier 3 would necessitate a considerable elevation in the scope and breadth of our field measurements, a venture beyond the constraints of our current research project (Schroeder *et al*., 1997).

Two peer-reviewed allometric models and two BEF models were adopted on the basis of their relevance to our study area and focal species. They are as follows:

1. The BEF model used for estimating the biomass in a study conducted by Ganatsas *et al*. (2022) in the 77-year-old oak forest (dominated by *Quercus frainetto* and is in the process of conversion from coppice to high forest) of Cholomon Mountain in Chalkidiki, northern Greece was:

   $B=v\times BEFD$,

   where, 'B' refers to the aboveground tree’s biomass (t), 'v' refers to the aboveground tree’s volume over bark ($m^3$), and 'BEFD' refers to the Biomass Expansion Factor with the inclusion of wood Density which is equal to 1.011.

2. The allometric model used for estimating the biomass in the study conducted by Manolis *et al.* (2016) in the Gorgiani oak forest (dominated by *Quercus frainetto* with other oak species present sporadically) in Grevena, northwestern Greece, was:

   $B=35.3660\times d^{2.9902}$,

   where, 'B' refers to the aboveground tree’s biomass (gr), and 'd' refers to the class of diameter at breast height (DBH) over bark (cm).

3. The allometric model used for estimating the biomass in the study conducted by Zianis *et al*. (2016) in the Taxiarchis experimental forest, consisting of the same tree species as in the study area of Ganatsas *et al*. (2022), located on the Chalkidiki peninsula, northern Greece was:

   $B=0.1341\times d^{2.47}$,

   where, 'B' refers to the aboveground tree’s biomass (gr), and 'd' refers to the class of diameter at breast height (DBH) over bark (cm).

4. The BEF model used for estimating the biomass in the study conducted by Penman *et al*. (2003) was:

   B=v×BWD×BEF,

   where, 'B' refers to the aboveground tree's biomass (t), 'v' refers to the aboveground tree's volume over bark ($m^3$), 'BWD' refers to the basic wood density (kgr of dry weight per $m^3$ of green volume = 700, FAO, 2023), and 'BEF' refers to the biomass expansion factor, with values ranging from 1.15 to 3.2. The upper limit of the range represents young forests or forests with low growing stock while the lower limit represents mature forests or those with high growing stock (Penman *et al*., 2003).

***Input data***

The application procedure for the four models was as follows: For the calculation of the minimum sample size required (minimum number of sample areas required) for a finite population with size $n_p$ in the areas of deciduous oak forests in the study area (the area of responsibility of the XFS), the formula of Stauffer (1982) was applied:

$$n_p = \frac{Nt^2cv^2}{Ne^2 + t^2cv^2},$$

where, 'N' stands for size of finite population (= 1909) of deciduous oak stands; 't' stands for value of student (t) distribution, for a probability of 5% and 1 (pre-sample size) degree of freedom; 'cv' stands for coefficient of variance of the pre-sample; 'e' stands for desired precision (acceptable error) = 0.10 (arbitrarily defined).

As a pre-sample (pilot sample), we defined 10 values of the total oak wood stock ($m^3$), selected at random from the 1909 deciduous oak polygons, as recorded in the vegetation polygon mapping of the XFS' s management plans. Random sampling of the 10 pre-sample values was repeated 599 times (Wilcox, 2001). As per the above formula, a total of 48 sampling points had to be distributed on the map. The distribution was done using the Collect Earth Grid Generator Tool (OFCA, nondated). This tool enables the automated generation of spatially distributed sampling points, ensuring a systematic and unbiased sample selection process.

***Sampling process involved***

1. ***Integration of tabular data with spatial maps:*** The management plans provided detailed forest inventory data, including the number of trees per diameter at breast height (DBH) class, volume over bark, and area per stand block. These tabular data were linked with spatial maps of the forest stands obtained from the XFS, allowing us to associate specific forest stands with their corresponding inventory data.

2. ***Selection of representative strata:*** Forest stands were categorized into strata based on their DBH classes and wood stock amounts to ensure that the sampling points covered the entire range of variability within the study area. This stratified sampling approach ensured that each stratum of the forest ecosystem, representing different age groups and biomass densities, was adequately sampled.

3. ***Mapping and distribution of sampling points****:* Using the Collect Earth Grid Generator Tool, we distributed the 48 sampling points across the study area. Each sampling point was precisely mapped and associated with a designated block and stand within the boundaries of the XFS. The use of high-resolution satellite imagery from Google Earth Pro facilitated the accurate placement and verification of these points.

4. ***Data collection from each sampling point****:* From each sampling point, we collected detailed forest inventory data, such as the number of trees per DBH class and volume over bark for the calculation of biomass estimates. For instance, the total biomass estimates for Sampling Point 12 within stand 'd' of Block 11 in the Thermes-Satres complex were calculated using the aforementioned models as highlighted in Table 1.

**Table 1: Biomass calculations through Ganatsas *et al.* (2022), Manolis *et al.* (2016), and Zianis *et al.* (2016) models**

| DBH class over bark 'd' (cm) | No. of trees 'N' in 0.1 ha sample plot | Volume over bark 'v' ($m^3$); Area 'A' (ha) | Biomass via Ganatsas *et al.* (2022) B=v × BEFD/A (t/ha) | Biomass via Manolis *et al.* (2016) $B=(35.3660 \times d^{2.9902} \times N) \times 0.001$ (kgr) | Biomass via Zianis *et al.* (2016) $B=0.1341 \times d^{2.47} \times N$ (kgr) |
|---|---|---|---|---|---|
| 10 | 21 | | | 726.1147139 | 831.09 |
| 12 | 5 | | | 298.2110342 | 310.44 |
| 14 | 5 | | | 472.8332395 | 454.29 |
| 16 | 7 | | | 986.8327517 | 884.51 |
| 18 | 8 | | | 1603.9535030 | 1352.20 |
| 20 | 4 | 1498; 36.16 | **41.88** | 1098.9699740 | 877.07 |
| 22 | 8 | | | 2922.7268530 | 2219.74 |
| 24 | 4 | | | 1895.6300690 | 1375.97 |
| 26 | 1 | | | 602.0592700 | 419.19 |
| 28 | 1 | | | 751.4115873 | 503.40 |
| 30 | 1 | | | 923.5787213 | 596.92 |
| | | | | $B = \frac{\sum(726.1 + 298.2 + \cdots) \times 0.001}{0.1}$ = 122.82 t/ha | $B = \frac{\sum(831.1 + 310.4 + \cdots) \times 0.001}{0.1}$ = 98.25 t/ha |

Based on the results displayed in Table 1 above, the estimated total biomass for the Sampling Point 12 was:

- 41.88 t/ha, using the Ganatsas *et al*. (2022) model;
- 122.82 t/ha, using the Manolis *et al*. (2016) model; and
- 98.25 t/ha, using the Zianis *et al*. (2016) model.

Finally, the method of biomass estimation by Penman *et al*. (2003) was implemented with the following approach:

The volumes of oak wood and the corresponding areas per stand block were extracted from the management plans' yield tables. We calculated the biomass at each sampling point, applying the BEF values against the volume data. For example, for the same sampling point (i.e., sampling point 12, block 11, stand d, in the Thermes-Satres complex), we determined the biomass with BEF as shown in Table 2.

**Table 2: Biomass calculations through BEF (Penman *et al*., 2003)**

| Volume over bark ($m^3$) | BEF (Penman *et al*., 2003) | Area (ha) | Biomass via BEF B=v×BWD×BEF×0.001/area (t/ha) |
|---|---|---|---|
| 1498 | [1.15 to 3.2] | 36.16 | [33.35 to 92.80] |

Based on the data presented in Table 2, the estimated biomass through the BEF method within the Sampling Point 12 ranged from 33.35 to 92.80 t/ha, accounting for the varying growth stages of the oak trees.

## Results

The average aboveground biomass was estimated at 103.807±16.41 t/ha, 242.946±47.09 t/ha, and 165.734±25.79 t/ha using the models of Ganatsas *et al*. (2022), Manolis *et al*. (2016), and Zianis *et al*. (2016), respectively. Using the BEF of Penman *et al*. (2003), the average aboveground biomass was estimated to be within the limit of 82.655±13.06 t/ha (lower limit BEF=1.15) to 229.997±36.35 t/ha (upper limit BEF=3.2). The comparison between the tested biomass estimation models is given in Figure 3.

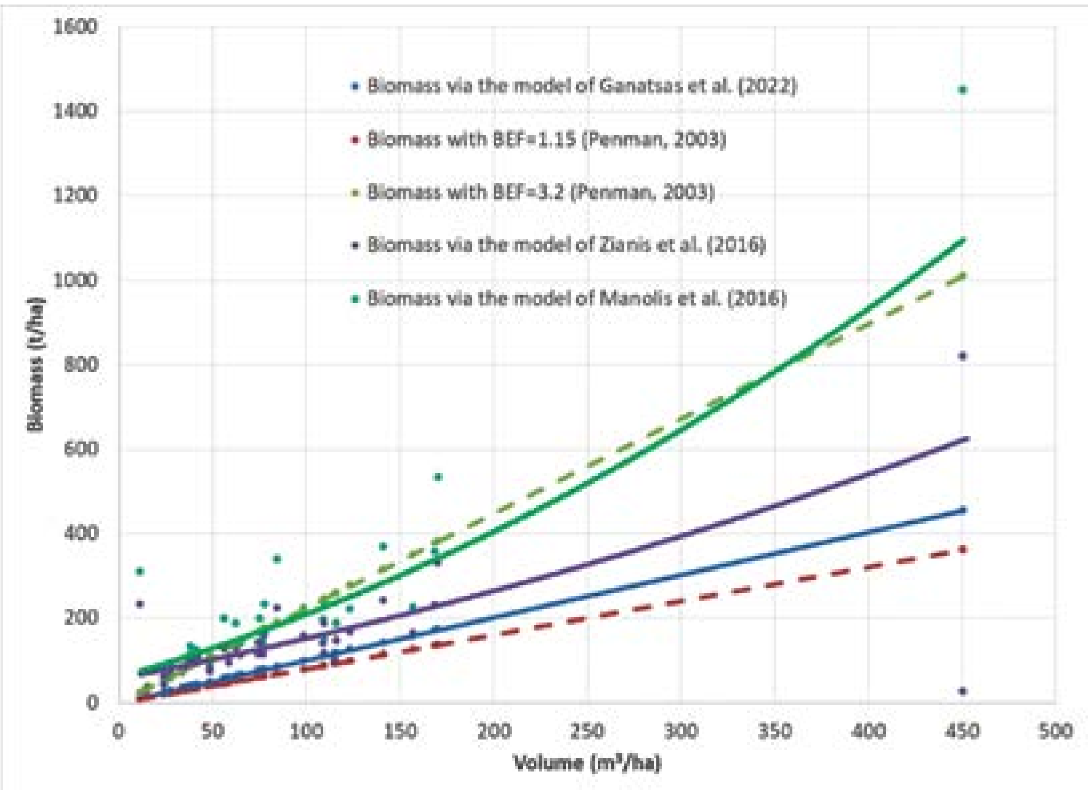


**Figure 3: Comparison between the tested biomass estimation models.**

The examination of the forest structure of our study area, with the distribution among DBH classes of the trees in the forest's stands (Figure 4), clearly indicated that the stands were young, thus having a high net productivity. Trees within these young stands were in an ascendant phase of their growth, marked by higher NPP and, hence, a significant accumulation of biomass.

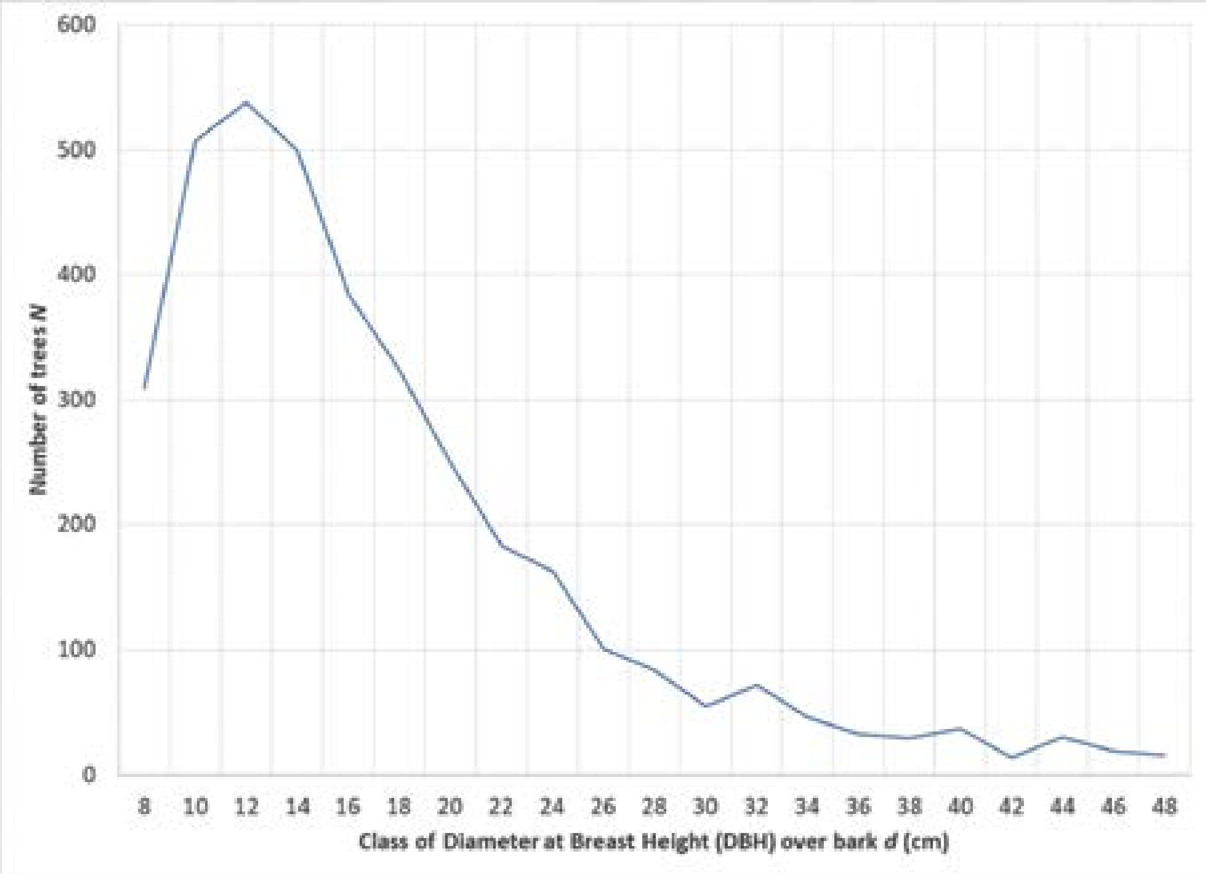


**Figure 4: DBH distribution of the stands.**

## Discussion

Our study evaluated the applicability of the biomass models proposed by Ganatsas *et al.* (2022), Manolis *et al.* (2016), and Zianis *et al.* (2016) to a forest area managed by the XFS. The Manolis *et al.* (2016) model, approximating biomass with a biomass expansion factor (BEF) of 3.2, emerged as the most accurate for our assessment. This can be attributed to its ability to account for the youthful vigor of the stands, which is consistent with the structure of the forests within our study area.

An interesting observation from our study was that only 4 out of 48 sampling points represented high-volume stands, each exceeding 400 m³/ha (Sampling Points: 8, 35, 55, and 60). These high-volume stands exhibited significant deviation between the biomass estimates of different models. Conversely, in low-volume stands, the deviation between the models was considerably smaller. For these stands, the biomass estimates showed greater consistency, reflecting the homogeneity in their structure.

These insights underscore the necessity of selecting and applying the appropriate allometric models based on forest structure and growth stage. Failure to do so can lead to significant errors in biomass estimation, particularly in heterogeneous forest landscapes like those managed by the XFS. Models by Zianis *et al.* (2016) and Ganatsas *et al.* (2022) are calibrated more towards the biomass estimation of mature stands and, therefore, fall short in our case.

Primary productivity is integral to forest ecosystems, as it encapsulates the photosynthetic activity of plants, which is instrumental in biomass accumulation. This process forms the cornerstone for the net primary productivity (NPP) of a forest by reducing gross photosynthetic carbon capture by the energy expended in autotrophic respiration and losses due to plant tissue mortality (Chapin *et al.*, 2011). NPP thus becomes a critical driver of organic carbon accrual in forest ecosystems, marking the difference between the amount of carbon assimilated through photosynthesis and that used or lost in respiration and decay processes (Clark *et al*., 2001).

The distribution of trees across various DBH classes is a fundamental component influencing NPP and, consequently, aboveground biomass. Forest structure encompasses various aspects such as tree density, size, age distribution, species composition, and the spatial arrangement of trees. A commonly used structural parameter is the distribution of trees among DBH classes, revealing productivity patterns across forest growth stages (Ryan *et al*., 2004; Stephenson *et al*., 2014). In young stands, characterized by a greater number of small-diameter trees, active growth and high NPP are evident. As forests age, the distribution typically shifts towards fewer larger-diameter trees, signifying a mature forest where NPP may level off or decrease as biomass accumulation slows (Odum, 1969; Luyssaert *et al*., 2007).

Our study area, dominated by young forests, showed rapid biomass accrual, making it apt to apply a BEF near the upper end of the range (Jenkins *et al*., 2003). In contrast, in mature forests with a more scattered distribution of large-diameter trees, a lower BEF might be more appropriate (Luyssaert *et al*., 2007). This is evident from our high-volume stands where the selected models showed larger deviations, indicating that the models suited for younger forests provided more accurate estimates.

Accurately gauging forest biomass requires an understanding of both NPP and the forest's structural dynamics, particularly when considering how the distribution of trees across DBH classes can reflect the growth phase and productivity of the forest. BEFs must be tailored to the specific structure of each forest—acknowledging that early-growth, dense stands rich in smaller DBH classes are structurally different from older, more evenly distributed stands with larger DBH trees. The tailored application of BEFs, based on forest structure, is not merely a theoretical exercise; it embodies a critical decision with tangible impacts on carbon budgeting and the assessment of a forest's ecological status and conservation value. It implicates management strategies, sustainability considerations, and carbon accounting practices within the framework of global efforts to mitigate climate change (Canadell & Raupach, 2008).

## Conclusion

This research aimed to identify the most appropriate model for predicting forest biomass in the oak-dominated ecosystems within the Xanthi region, using established models as benchmarks. Besides the relevance of a model to another study region and focal species, the structure of the studied forest plays a crucial role in biomass estimation. Our study area is characterized by young stands with a majority of smaller diameter trees, indicating high net primary productivity (NPP). Such characteristics necessitate the application of a BEF closer to the higher end of its range, which is suitable for young, actively growing stands (Penman *et al*., 2003). A comparison of allometric models, therefore, favors the use of the model proposed by Manolis *et al*. (2016).

Consistent with the tiered approach for model selection advocated by the IPCC, our analysis underscores the necessity of matching allometric models to the forest's structural attributes to ensure accurate biomass estimates. The suitability of the model of Manolis *et al*. (2016) for young stands implies that our study area possesses considerable potential for future biomass yield and carbon sequestration. This has significant implications for sustainable forest management, wherein accurate biomass estimates are crucial for formulating strategies that enhance the carbon storage potential of forests and contribute to climate change mitigation.

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## Author's contribution statement

**K. Kitikidou**: Research ideas, develop the research tools and methods, data analysis, revision of the research findings and manuscript preparation.

**E. Milios**: Research ideas, develop the research tools and methods, data analysis, revision of the research findings and manuscript preparation.

**K. Radoglou**: Research ideas, review and editing.

## Data availability

The data collected for this study is available from the ForOaks Project's official website- https://foroaks.fmenr.duth.gr/

## Conflict of Interest

The authors declare no conflict of interest.

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