SYLWAN 168 (2): 71-91, February 2024
https://doi.org/10.26202/sylwan.2023116
Journal homepage: https://sylwan-journal.pl

ORIGINAL PAPER

Effect of stand characteristics and environmental factors on the volume increment of oak in Poland

Hoang Duong Xo Viet(1, 2), Luiza Tymińska-Czabańska(1), Sławomir Konopa(1),
Jarosław Socha(1)✉

(1) Department of Forest Resources Management, Faculty of Forestry, University of Agriculture in Krakow, Al. 29 Listopada 46, 31-425 Krakow, Poland

(2) Faculty of Forestry, University of Agriculture and Forestry, Hue University, Hue 530000, Vietnam

ABSTRACT

Volume increment is a valuable indicator of the growth and performance of stands over time. It allows forest managers to assess forest productivity and indicate changes in growth conditions. In forestry practice, growth and productivity models can be developed by integrating volume increment data with environmental factors. The primary objective of this study was to develop a generalized additive model that would explain the influence of tree characteristics, climate and topography on oak volume increment. Our findings underscored the significant impact of basal area, age, height, and relative spacing index on the periodic annual volume increment (PAIv) of oak in Poland. We found that temperature, precipitation, slope and soil type within the study area also had significant effects on PAIv. The developed model explained approximately 43.8% of the variance of the PAIv. Notably, when applied to specific natural forest regions, the explanatory capacity of the model increased significantly, reaching around 64.4%. For smaller areas such as natural forest regions, PAIv was mainly determined by stand characteristics and less influenced by site factors such as slope and climate. This enhanced accuracy enhances its practical value and underscores its utility in distinct forest management contexts.

KEY WORDS

environmental effect, forest productivity, GAM, NFI, periodic volume increment

Introduction

Forest volume increment plays a vital role in forest research and management. Understanding volume increment supports managers in assessing forest productivity and growth dynamics for effective harvesting and management decisions. The volume increment describes the average volume growth of the stand over a given period and varies with stand age (Vanclay, 1994; Yu *et al.*, 2017). It also shows the response of the stand to site conditions such as nutrition, moisture, radiation and temperature (Pretzsch, 2010; West, 2014; Yu *et al.*, 2017).

Volume increment is a useful indicator of the growth rate and performance of stands over time (Vanclay, 1994). It is an important variable in predicting productivity, as numerous studies have consistently demonstrated a relationship between volume and productivity (Tomter *et al.*,

---

✉e-mail: jaroslaw.socha@urk.edu.pl

Received: 22 December 2023; Revised: 7 March 2024; Accepted: 8 March 2024; Available online: 18 April 2024

2016; Gasparini *et al.*, 2017; Wang *et al.*, 2019; Bayat *et al.*, 2021; Ábri and Rédei, 2022). Volume growth patterns also allow researchers to assess the productivity of different forest types, evaluate the effectiveness of silvicultural treatments and compare growth rates between different stands or regions (Río and Sterba, 2009; Allen *et al.*, 2021). Changes in volume increment can serve as indicators of shifts in forest conditions, potentially signifying the influence of pests, diseases, or unfavorable environmental factors. Such information holds great value in monitoring the response of forest stands to environmental changes, facilitating early detection of potential risks, and enhancing our understanding of forest ecosystem dynamics (Gauthier *et al.*, 2015; Coops *et al.*, 2020; Wu *et al.*, 2020). Volume increment is also directly related to the amount of wood and biomass produced by a stand (West, 2015). It provides an auxiliary variable to quantify the amount of carbon stored in trees and forest ecosystems. Therefore, estimating volume increment is critical for forecasting future timber supply, understanding the carbon sequestration potential of the stand, planning harvesting operations, and optimizing rotation lengths for different tree species and management strategies (Krug, 2019; Trouillier *et al.*, 2020; Stokland, 2021).

Growth and productivity models are necessary tools in forest management (Vanclay, 1994). In forestry practice, researchers can develop models by integrating volume increment data with other environmental factors such as soil properties, climate variables and other site factors to predict the productivity of the forest sites. A study conducted in northeastern Germany shed light on the intricate relationship between climate change and tree growth dynamics. Specifically, the study revealed that common beech *Fagus sylvatica* L. and pedunculate oak *Quercus robur* L., two prominent tree species in the region, exhibit noticeably slower growth rates when confronted with the challenges of drier and warmer conditions driven by climate change (Bauwe *et al.*, 2015). Another noteworthy study provided a nuanced perspective on the complex interplay between climate and tree development. The analysis demonstrated that climate change initially bestows a favorable impact on the periodic volume increment of several tree species, including Scots pine *Pinus sylvestris* L., European beech and oak. This positive influence is observed throughout the first phase of the study, spanning until 2030. However, this effect decreases or even reverses over time (until 2070) (Albert *et al.*, 2018). Fortin (2019) also found that climate change caused some tree species in French stands to decrease in volume increment from 1 to 5%. These studies simulate the development of forests under different climate change or management scenarios, allowing stakeholders to assess the long-term impact of environmental factors on the stands.

Oak forests are widespread across Europe and are considered one of the most important forest types in the region (Vospernik *et al.*, 2023). Two species of oak are dominant in Polish forests: pedunculate oak and English oak *Quercus petraea* (Matt.) Liebl., known as sessile oak. These species exhibit several shared characteristics: they are robust trees with a wide ecological range, capable of dominating forests in terms of both quantity and size, particularly at lower to mid-elevations (Petritan *et al.*, 2012; Eaton *et al.*, 2016). Oak forests are known for their exceptional biodiversity and ecological value, providing habitat for numerous plant and animal species (Eaton *et al.*, 2016), while being of great economic importance in Europe and particularly in Poland (Xo Viet *et al.*, 2022).

Therefore, the aim of this study was to identify the stand characteristics and environmental factors that significantly affect oak volume increment. We used the large dataset from the Polish National Forest Inventory (NFI) from 2005 to 2019 to develop models explaining the influence of tree characteristics, climate and topography on oak volume increment. The study may provide useful information for forest conservation and management activities.

Materials and methods

Sample plot data. For this study, we utilized data between 2005 and 2019 from NFI activities conducted in Poland. The measurement period began in 2005, and the duration of each measuring cycle was equally 5 years. We collected 1945 sample plots in mixed stands where oak species predominate of three cycles (Fig. 1). The first period lasted from 2005 to 2009, the next was 2010-2014, and the third was 2015-2019. These two oak species are comparable in growth and productivity (Tymińska-Czabańska *et al.*, 2021). They are also morphologically similar, so it is sometimes difficult to distinguish them accurately in the field, or they are not distinguished during forest inventories. Therefore, in this analysis, we did not separate the two oak species. The NFI primary points are the nodes of the 4×4 km grid. Sample plots were established in equal arm L-shaped tracts with five points spaced 200 m apart. Measurements were carried out on two types of concentric circular sample plots of suitable sizes for the inventory characteristics. The age of the stands was determined based on data stored in the Polish forest data bank. Sample plots were representative of the entire geographic range, site conditions, and distribution in various natural forest regions in Poland, which are adopted as the unit of regionalization in Poland (Zielony and Kliczkowska, 2012). Natural forest regions are characterized by different natural attributes such as changes in climatic and geological factors and natural ranges of major forest species.

On each sample plot, the following properties were measured and calculated (Table 1):

- QMD: Quadratic mean diameter at the breast height,
- TH: Top height is defined as the mean height of the one hundred thickest trees per hectare,

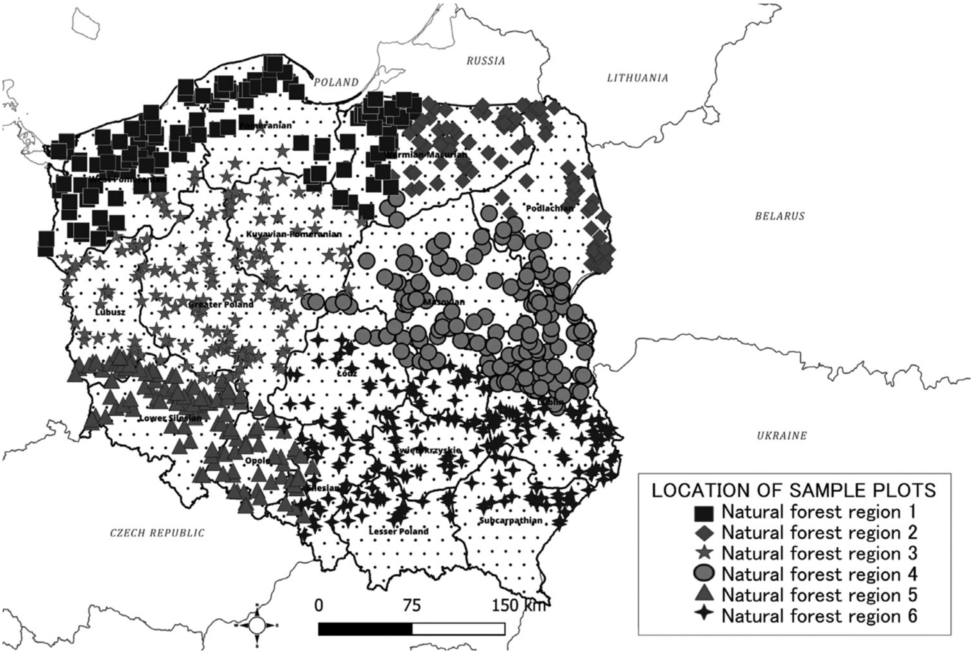

Fig. 1.
Location of NFI oak-dominated sample plots in Poland

Table 1.
Basic characteristics of the sample plots

Variable	Mean	Minimum	Maximum	Standard Deviation
		Predictor Variable		
Age [years]	72.93	9.00	205.00	38.47
QMD [cm]	30.47	7.00	135.30	16.35
TH [m]	20.93	3.40	37.95	7.25
N [trees/ha]	636	20	2850	359
V [m^3/ha]	195.74	0.13	709.29	164.81
BA [m^2/ha]	15.56	0.11	64.10	9.91
RSI [%]	24.93	8.83	59.08	25.89
		Dependent Variable		
PAIv [m^3/ha/year]	6.62	0.03	23.42	4.52

– N: Density is defined as number of trees per hectare,
– BA: Total basal area,
– V: Stand volume,

$$V = v \cdot N \tag{1}$$

where:
v is the tree volume;
N is the density,

$$v = g \cdot h \cdot f \tag{2}$$

where:
h – tree height;
g – cross-sectional area of trees at breast height;
f – form factor, referring to the tree's characteristic shape and is the scale factor of the cylinder volume to the actual merchantable tree volume.

We applied the formula $f$or form factor of Bruchwald *et al.* (2000).

$$f = 0.5441 \cdot DBH^{-0.0415}\left(\frac{DBH-3}{0.9549+0.9439\cdot(DBH-3)}\right) \tag{3}$$

– RSI: The relative spacing index is defined as the percentage, between the average distance among trees and the top height of the stand (Meredieu *et al.*, 2002; Socha *et al.*, 2020).

$$RSI = \frac{AS}{TH}\cdot 100 = \frac{10^4 \cdot \sqrt{\frac{2}{N\cdot\sqrt{3}}}}{TH} \tag{4}$$

where:
AS – average tree spacing,
TH – top height,
N – density. To calculate AS using N, trees were assumed to be placed on a triangular grid.

– PAIv: The periodic annual volume increment is defined as the rate of volume growth of tree or stand over some period of time (Bayat *et al.*, 2021; Ábri and Rédei, 2022).

$$PAIv = \frac{V_E + V_H - V_B}{T_j - T_i} \tag{5}$$

where:

V_E – volume at the end of the period;

V_B – volume at the start of the period;

V_H is the average volume harvested or died (mortality and cut) during the same period;

T_i is the year at the start of the period;

T_j is the year at the end of the period.

In this study, we calculated the PAIv of the stands over a period of 5 years.

TOPOGRAPHIC AND CLIMATE DATA. We used the European Digital Elevation Model (EU-DEM) for Poland to describe the slope and altitude of sample plots (Table 2).

Table 2.

Soil types and geological types estimated for the sample plots

Type of soil	1. Luvisols / pseudopodsols / pseudogleys developed from loess; 2. River alluvial silts, clay and clayey; 3. Luvisols / pseudopodsols / pseudoglias, formed from sedimentary rocks; 4. Initial and poorly developed soils; 5. Rusty soils / podzolic and podzolic soils developed from loose sands; 6. Rusty / cryptic podzolic and podsolic soils developed from clay sands; 7. River sand alluvial; 8. Luvisols / pseudopodsols / pseudoglias made of sands; 9. A complex of leached brown soils and loess soils as well as rendzinas made of sands and calcareous clays; 10. Podzolic soils and podzols developed from loose sands; 11. Gley, silt-clay, peat-gley, muck-gley and muck-gley soils; 12. Black and gray lands; 13. Proper and leached brown soils formed from clay and loess dusts; 14. Brown acidic and leached soils; 15. Carbonate rendzinas; 16. Proper and leached brown soils, developed from sands; 17. Soils made of peat; 18. Podzolic soils and podzols developed from lightly clayey sands and boulder clayey sands;
Type of geology	1. Loess; 2. Sandy loess and loess-like silts; 3. Outwash sands and gravels; 4. Fluvial sands, gravels, muds, peats and organic silts; 5. Conglomerates, graywackes, mudstones and subordinately of claystones and rhyolites; 6. Fluvial sands, gravels and silts; 7. Ice-dam clays, silts and sands; 8. Sandstones, conglomerates, mudstones and claystones, tuffs and coal; 9. Eolian sands, locally in dunes; 10. Conglomerates, graywackes, claystones, mudstones, limestones and greenstones; 11. Tills, weathered tills, glacial sands and gravels; 12. Limestones, marls, dolomites, limestones with flint, glauconitic mudstones and sandstones; 13. Sands, gravels and silts; 14. Limestones, dolomites, marls, oolitic limestones, claystones, locally mudstones, anhydrite and gypsum; 15. Variegated claystones, mudstones, sandstones, dolomites, limestones with gypsum, halite and anhydrites; 16. Organodetritic and sulphur-bearing limestones, gravels, sandstones and gypsum; 17. Migmatites and gneisses; 18. Limestones, marls, chalk, sandstones, mudstones; 19. Gneisses, granite gneisses and schists; 20. Limestones, chalk with flint, calcareous gaizes, marls, subordinate intercalations of sandstones and gaizes; 21. Peridotites, serpentinites, gabbros and diabases; 22. Amphibolites, gneisses, amphibole schists and diabases; 23. Basaltic rocks; 24. Claystones, mudstones, graywackes, tuffites and sandstones; 25. Limestones, marls, sandstones, calcareous gaizes with cherts, phosphorites; 26. Lake sands and silts; 27. Kame sands and silts; 28. Clays, silts, sands, gravels with lignite; 29. Limestones, marls, claystones, mudstones, conglomerates, sandstones, gaizes, sands intercalated with siderites; 30. Limestones, dolomites, marls, claystones, shales, sandstones, mudstones and conglomerates; 31. End moraine gravels, sands, boulders and tills; 32. Peat, gyttjas, lake chalk, clays, silts and sands, fluviolacustrine gravels and silts; 33. Sandstones, mudstones and claystones intercalated with siderites; 34. Sandstones, marls, conglomerates, claystones and iron-ore; 35. Deluvial loams, sands and loams with rock rubbles; 36. Gaizes, limestones, calcareous gaizes, glauconitic sands and sandstones, marls, silts and clays; 37. Clays, silts and sands containing phosphorites and ambers, locally lignite; 38. Alluvial fan sands and gravels; 39. Esker sands, silts and gravels; 40. Lakes and main rivers; 41. Lake sands, silts, clays and gyttjas

To determine the type of soil and geology (Table 2), we used the soil map and geological map of Poland at a scale of 1:500,000 (Budzyńska *et al.*, 2001).

We acquired the climate data from the Institute of Meteorology and Water Management stations located in Poland for the period 2005-2020. We used Qgis 3.28.2 software to interpolate climate data. Based on the interpolated values, 19 bioclimatic indicators (Table 3) were calculated for each sample plot using 'dismo' package in R program (R Core Team, 2021).

Model development. This study aimed to develop a model explaining the dependence of the periodic annual volume increment on climate, topography as well as the characteristics of the stand. When developing linear models, multicollinearity is usually a severe problem. Collinearity can lead to unreliable models and reduce the predictive power of the model. To solve this problem, we used the variance inflation factor (VIF) for feature selection. VIF is used to detect multicollinearity among predictors in multiple linear regression models (Murray *et al.*, 2012; Cheng *et al.*, 2022). When the predictors are highly collinear, the higher the VIF values are determined. Many studies showed that a VIF value exceeding 5 indicates a problematic amount of collinearity (Mendes *et al.*, 2008; James *et al.*, 2013; Melnychuk *et al.*, 2017). We used the 'mgcv' package in R program to calculate the VIF values. We calculated VIF values for all predictors and excluded the variable with the highest VIF, repeating the process until all the predictors had VIF values around 5.

The VIF for each variable can be calculated using the formula:

Table 3.

Characteristics of the climate variables estimated for sample plots

Variable	Variable description	Mean	Minimum	Maximum	Standard Deviation
BIO1	Annual Mean Temperature [°C]	9.35	6.46	12.07	1.05
BIO2	Mean Diurnal Range (mean of monthly (max temp – min temp)) [°C]	24.26	18.69	28.06	1.39
BIO3	Isothermality (BIO2/BIO7) (×100) [%]	47.96	42.15	53.82	2.29
BIO4	Temperature Seasonality (standard deviation×100) [%]	874.29	712.24	1072.16	74.65
BIO5	Max Temperature of Warmest Month [°C]	32.91	29.02	36.05	1.04
BIO6	Min Temperature of Coldest Month [°C]	–18.05	–26.52	–10.59	3.33
BIO7	Temperature Annual Range (BIO5-BIO6) [°C]	50.95	40.56	59.27	3.24
BIO8	Mean Temperature of Wettest Quarter [°C]	17.46	8.85	21.39	1.84
BIO9	Mean Temperature of Driest Quarter [°C]	4.06	–3.05	12.66	2.41
BIO10	Mean Temperature of Warmest Quarter [°C]	19.66	16.77	21.84	0.72
BIO11	Mean Temperature of Coldest Quarter [°C]	–1.93	–7.44	2.23	2.19
BIO12	Annual Precipitation [mm]	652.67	460.29	1123.81	78.52
BIO13	Precipitation of Wettest Month [mm]	120.86	72.74	226.74	21.94
BIO14	Precipitation of Driest Month [mm]	12.10	4.63	27.39	3.54
BIO15	Precipitation Seasonality (Coefficient of Variation) [%]	62.04	44.46	87.17	7.98
BIO16	Precipitation of Wettest Quarter [mm]	283.51	173.02	475.38	44.49
BIO17	Precipitation of Driest Quarter [mm]	81.53	47.40	131.99	12.03
BIO18	Precipitation of Warmest Quarter [mm]	255.71	155.94	426.25	42.22
BIO19	Precipitation of Coldest Quarter [mm]	110.20	52.97	197.39	19.39
Slope	degrees	2.28	0.04	19.16	1.99
Altitude	Altitude above sea level [m]	167.46	4.54	503.69	68.89

$$VIF_{Xj} = \frac{1}{1 - R^2_{X_J|X_{-J}}} \tag{6}$$

where:

$R^2_{X_J|X_{-J}}$ is R^2 from a regression of X_J onto all the other predictors.

We used the variable importance plots (VIP) function of the 'VIP' package in R program to evaluate the importance of the predictors participating in the model. This is a general framework for building variable importance plots from different types of machine learning models in R program (Greenwell and Boehmke, 2020). The selected variables were used to develop the model.

Among many methods for building models, Aertsen *et al.* (2010) pointed out the effectiveness of the Generalized Additive Model (GAM). GAMs are more flexible than general linear models because the independent and dependent variables are not assumed to be linearly related. Unlike general linear models, GAM uses a combination of both linear and nonlinear functions to describe the relationship between the dependent and predictor variables. GAM allows the researchers to model highly complex non-linear relationships with a large number of potential predictors. (Larsen *et al.*, 2015; Hastie and Tibshirani, 2017; Wood, 2017; Tymińska-Czabańska *et al.*, 2021).

The structure of GAM is:

$$g(E(Y)) = \alpha + s_1(x_1) + \cdots + s_p(x_p) \tag{7}$$

where:

Y – response variable;

$E(Y)$ – denotes the expected value;

g(Y) – denotes the link function that links the expected value to the predictor variables $x_1, ..., x_p$; and $s_1(x_1), ..., s_p(x_p)$ denote smooth, nonparametric functions.

To determine significant variables which should be included in the GAM model, we used the coefficient table, plots and the ANOVA function to examine the deviation of GAM through the 'mgcv' package in the R program. In describing the data set, the model should be as simple as possible. We used the ANOVA function to test whether a complex model with an additional variable would capture the data significantly better than a model without that variable. If the p-value obtained was sufficiently low (we used the 0.05 level), we chose a more complex model with the additional variable. Otherwise, we chose the simpler model without the additional variable if the p-value was not less than 0.05.

10-fold cross-validation was used to analyze model performance and possible over-fitting in resulting of the adjusted R^2. This method randomly divided the data into 10 parts, then 9 were used for training and 1 for testing. This process was repeated 10 times, with a different tenth being reserved for the test each time. The method was carried out using the R language packages 'gam' and 'caret' (Zacharski, 2018). In the final step, we checked the performance of the model using:

Mean absolute error:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \tag{8}$$

Root mean square error:

$$RMSE = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n}} \tag{9}$$

Adjusted coefficient of determination:

$$R^2_{adj} = 1 - (1 - R^2)\frac{n-1}{n-p-1} \tag{10}$$

where:

y_i – terms are the observed values,
$\hat{y}_i$ – terms are the model values,
n – number of observations,
p – denotes the number of parameters used in the model,
R^2 – is the coefficient of determination.

Results

The results of calculating the VIF values indicated the variables that could cause collinearity in the model. These variables were therefore removed from further modelling (Table 4).

We found different effects of variables on the PAIv of oak stands (Fig. 2). The basal area, age and geology had the strongest impact on PAIv.

Table 4.
Selected predictors to develop the volume increment model for oak

Variables	Unit	Use formodeling
Age	years	√
TH	m	√
QMD	cm	×
V	m^3/ha	×
BA	m^2/ha	√
RSI	%	√
BIO1	°C	×
BIO2	°C	√
BIO3	%	√
BIO4	%	×
BIO5	°C	×
BIO6	°C	×
BIO7	°C	×
BIO8	°C	√
BIO9	°C	√
BIO10	°C	√
BIO11	°C	×
BIO12	mm	×
BIO13	mm	×
BIO14	mm	√
BIO15	%	×
BIO16	mm	×
BIO17	mm	√
BIO18	mm	√
BIO19	mm	√
Slope	degrees	√
Altitude	m	√
Soil type		√
Geology		√

√ – variable used for the model; × – variable unused for the model

We also established the approximate significance of each predictor variable for the PAIv of oak stand in the GAM model (Table 5).

Our results showed that when developing the GAM model for all selected variables, there are 7 significant predictors in the model: age, top height, basal area, slope, BIO8, BIO17, BIO18 (Table 5). After using ANOVA analysis to determine whether keeping other variables would improve the ability of the model to capture data, we noticed that for continuous covariates, the RSI variable significantly increased the explanatory ability of the model when it was added (ANOVA, $p<0.05$) (Table 6).

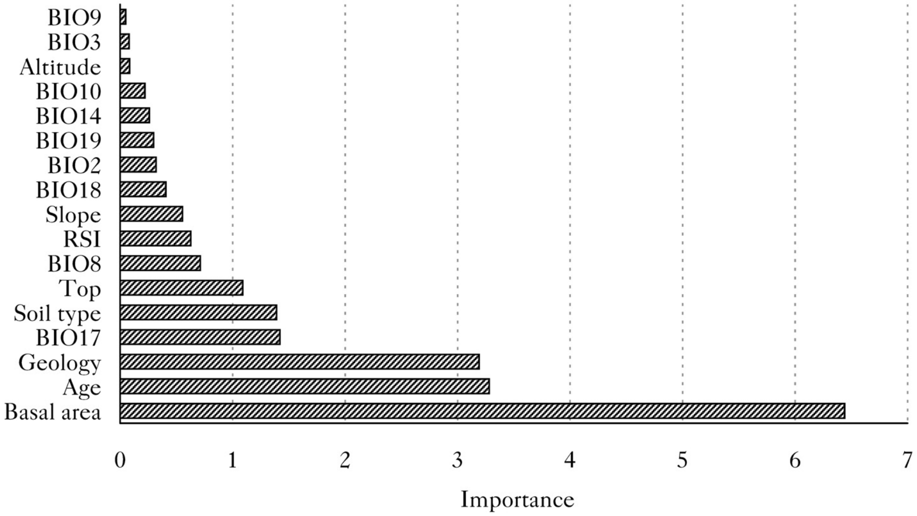

Fig. 2.

Significance of the predictor variables on the periodic annual volume increment of the oak stands

Table 5.

Approximate significance of predictor variables on the stand periodic annual volume increment described using the GAM model

Predictor Variable	Effective Degrees of Freedom	Reference Degrees of Freedom	F	p
Age	3.881	4.881	28.013	<0.0001
Top height	1.000	1.000	964.241	<0.0001
Basal area	2.963	3.842	5.704	0.0002
BIO18	2.480	3.169	3.521	0.0131
BIO8	3.854	4.824	2.440	0.0337
BIO17	6.421	7.611	2.341	0.0351
Slope	1.001	1.002	4.289	0.0385
RSI	2.954	3.697	1.500	0.1656
BIO2	1.965	2.543	1.570	0.1694
BIO14	1.000	1.001	1.607	0.2050
BIO10	1.000	1.000	0.734	0.3916
BIO3	1.002	1.004	0.267	0.6054
BIO19	1.887	2.427	0.211	0.7392
Altitude	1.000	1.000	0.084	0.7727
BIO9	1.000	1.001	0.047	0.8283

Table 6.

The results of testing the significance of covariates by comparing, using ANOVA, a simple GAM model with a GAM model augmented with the analysed variable

Simple Model (Number)	Extended Model (Number)	F	p
(1) Age, top height, basal area, slope, BIO8, BIO17, BIO18	(2) Age, top height, basal area, slope, BIO8, BIO17, BIO18, BIO2	2.2884	0.0669
	(3) Age, top height, basal area, slope, BIO8, BIO17, BIO18, BIO3	0.4205	0.5986
	(4) Age, top height, basal area, slope, BIO8, BIO17, BIO18, BIO9	1.9281	0.1055
	(5) Age, top height, basal area, slope, BIO8, BIO17, BIO18, BIO10	0.9965	0.3679
	(6) Age, top height, basal area, slope, BIO8, BIO17, BIO18, BIO14	2.3208	0.1136
	(7) Age, top height, basal area, slope, BIO8, BIO17, BIO18, BIO19	1.4394	0.2353
	(8) Age, top height, basal area, slope, BIO8, BIO17, BIO18, Altitude	1.1380	0.3284
	(9) Age, top height, basal area, slope, BIO8, BIO17, BIO18, RSI	2.3585	0.0399
(9) Age, Height, Basal area, Slope, BIO8, BIO17, BIO18, RSI	(10) Age, top height, basal area, slope, BIO8, BIO17, BIO18, RSI, Soil type	1.6380	0.0450
	(11) Age, top height, basal area, slope, BIO8, BIO17, BIO18, RSI, Geology	0.9496	0.5547

We continued to use ANOVA analysis for 2 categorical variables, soil type and geology, and found that only soil type was significant for the model (Table 6). From the analysis results, we developed a GAM model to explain the change in PAIv of oak stands with 9 predictor variables (Model 10: age, top height, basal area, RSI, BIO8, BIO17, BIO18, slope and soil type).

The significance level of the predictors (Fig. 2) showed the importance of basal area on PAIv of oak stands. We found that PAIv of oak stands increased significantly as basal area increased (Fig. 3a). The PAIv of the oak stands increased by about 3 m^3/ha/year with each 10 m^2/ha increase in basal area. We also noted a strong effect of stand age on PAIv. The PAIv of oak stands decreased significantly with stand age. For oak stands over 100 years old, the rate of decrease has slowed (Fig. 3b). The PAIv was influenced by the top height of the oak stand. However, once the top height exceeded 30m, the increase in top height no longer had a significant effect on PAIv (Fig. 3c). We demonstrated an increase in PAIv according to the relative spacing index (Fig. 3d). PAIv was observed to increase as RSI increases, particularly for the smallest and largest ranges of RSI values. The slightest effect of RSI influence was seen in the range of 20-35%.

We also noted the effect of climate on PAIv of oak stands. PAIv of oak stands tended to be stable when BIO17 was less than 110mm. Outside this range, PAIv increased slightly with the increase of BIO17 (Fig. 4a). Besides, the PAIv of oak stands slightly increased with the increasing of BIO18. However, when the BIO18 exceeded 270mm, this effect was no longer observed (Fig. 4b). In addition, the PAIv of oak stands was affected by the temperature. It decreased slightly when BIO8 was higher than 19°C (Fig. 4c).

The relationship of PAIv with soil type and topography was investigated in our study. When the slope exceeded 5 degrees, the PAIv showed a trend to decrease (Fig. 5a). Soil type

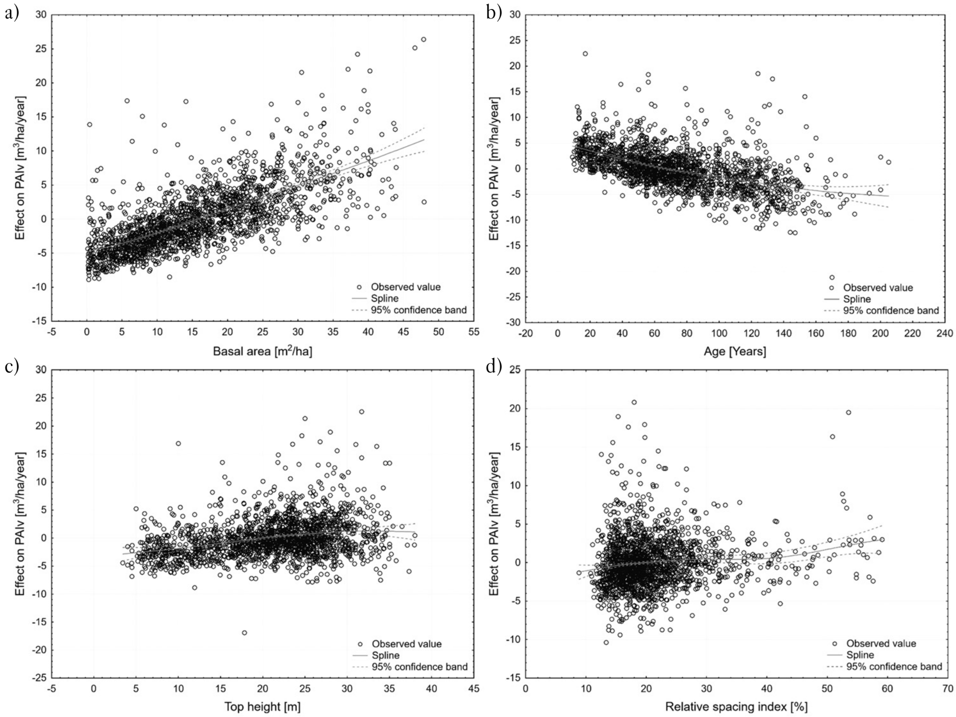

Fig. 3.

Partial effect of the basal area (a), age (b), top height (c) and relative spacing index (d) on the periodic annual volume increment of the oak stands

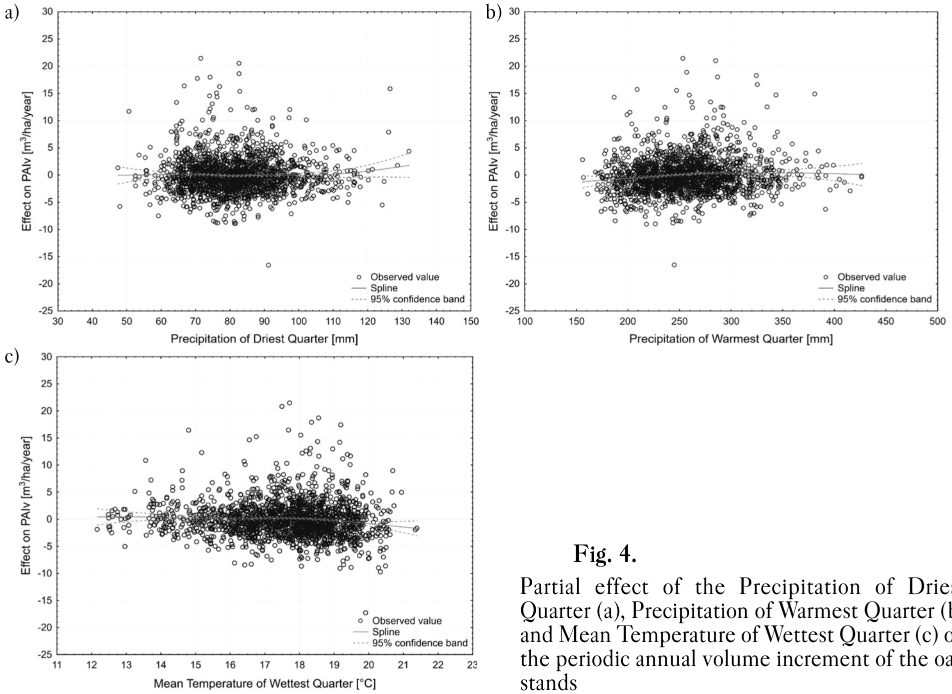

Fig. 4.

Partial effect of the Precipitation of Driest Quarter (a), Precipitation of Warmest Quarter (b) and Mean Temperature of Wettest Quarter (c) on the periodic annual volume increment of the oak stands also had an effect on PAIV. The highest PAIv was observed in stands growing on the black and gray lands (Fig. 5b).

The model based on 9 predictor variables (age, top height, basal area, RSI, BIO8, BIO17, BIO18, slope and soil type) had the highest R^2_{adj} while the mean absolute error of the model (MAE) and the root mean square error (RMSE) were lower than the other models (Table 7). This model explained about 43.8% PAIv variability. The mean absolute error of the model (MAE) was 2.41 m^3/ha/year and the root mean square error (RMSE) was 3.37 m^3/ha/year. R^2_{adj} calculated on the basis of the 10-fold cross-validation was 41.4%, indicating that the model overfitting was not a problem (Fig. 6). This points to the good predictive capacity of the model developed.

Additionally, using selected 9 predictor variables we developed models for natural forest regions in Poland. By using the GAM model for each specific natural forest region, we found that the predictive ability of the model increased significantly. In a specific region, site factors such as slope and climate had negligible effects on volume increment. By contrast, stand characteristics were the most critical factors influencing volume increment (Table 8).

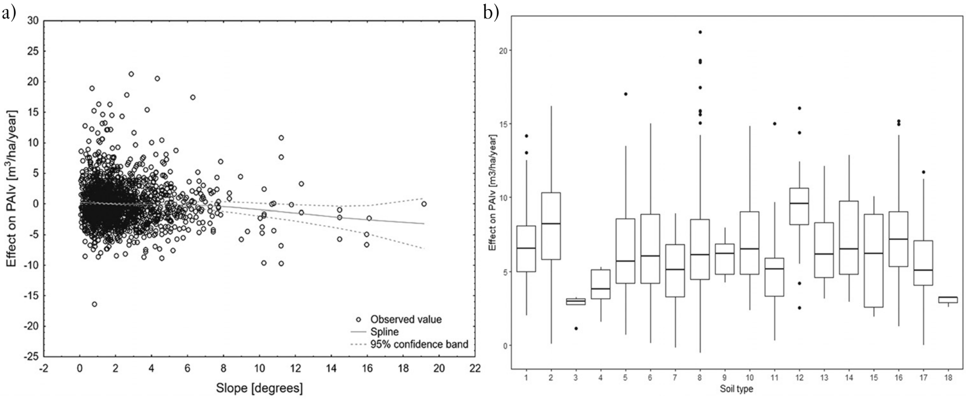

Fig. 5.

Partial effect of slope (a) and soil type (b) on the periodic annual volume increment of the oak stands (Soil type information in Table 2)

Table 7.

Statistical indicators of the models

Model (Number)	R^2 (adj)	Deviance explained	RMSE	MAE
(1) Age	2.6	2.75	4.47	3.41
(2) Age, top height	10.1	10.7	4.29	3.23
(3) Age, top height, basal area	41.9	42.2	3.45	2.48
(4) Age, top height, basal area, BIO8	42.2	42.5	3.44	2.47
(5) Age, top height, basal area, BIO8, BIO17	42.6	43.1	3.42	2.46
(6) Age, top height, basal area, BIO8, BIO17, BIO18	42.8	43.4	3.41	2.46
(7) Age, top height, basal area, BIO8, BIO17, BIO18, slope	43.1	43.7	3.40	2.45
(8) Age, top height, basal area, BIO8, BIO17, BIO18, slope, RSI	43.3	44.1	3.39	2.44
(9) Age, top height, basal area, BIO8, BIO17, BIO18, slope, RSI, soil type	43.8	44.9	3.37	2.41

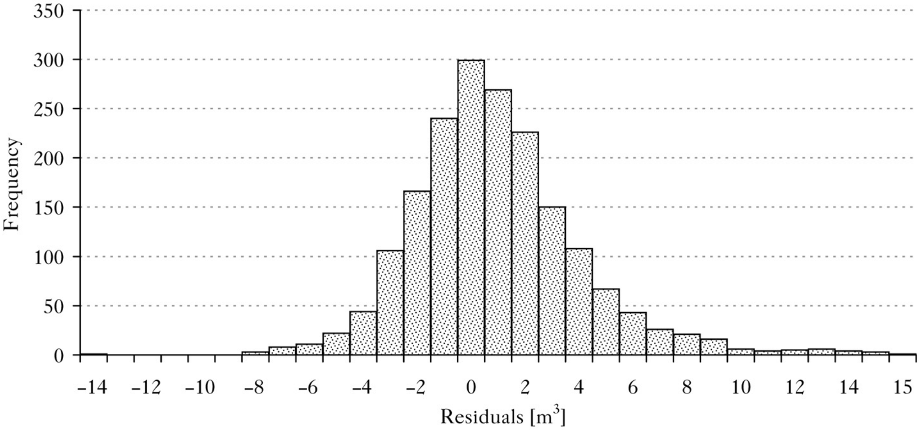

Fig. 6.
Histogram of the residual values of the GAM model

Table 8.
Approximate significance of predictor variables on the periodic annual volume increment described using the GAM model for different natural forest regions

Variable	Natural forest region					
	1	2	3	4	5	6
	P value					
Age	<0.0001	0.00254	<0.0001	<0.0001	0.0127	<0.0001
Top height	0.3615	0.04693	0.00434	0.00497	0.0993	0.0208
Basal area	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
RSI	0.4312	0.50792	0.47787	0.52581	0.4352	0.0831
Slope	0.1886	0.37079	0.30163	0.12889	0.0896	0.4674
BIO8	0.2417	0.37343	0.16380	0.23690	0.0779	0.2962
BIO17	0.0406	0.35954	0.54474	0.13520	0.8216	0.0509
BIO18	0.7604	0.57211	0.00163	0.12364	0.0482	0.3892
R^2 [adj]	60.23	50.86	47.39	64.44	59.39	48.07
MAE [m^3/ha/year]	2.34	2.04	2.66	1.76	2.49	2.36
RMSE [m^3/ha/year]	3.10	2.67	3.50	2.30	3.34	3.32

Discussion

This study indicated a strong relationship between PAIv and stand characteristics for oak. The results confirmed that age and basal area caused the greatest amplitude of change in PAIv of oak stands. The PAIv of oak stands increased by about 3 m^3/ha/year with each 10 m^2/ha increase in basal area and decreased by about 2.5 m^3/ha/year every 50 years. We also demonstrated that the volume increment of oak stands is affected by climate and topographic factors. The analysis showed a noticeable effect of the Wettest Quarter Mean Temperature on PAIv. The developed model predicted 43.8% of the variance of the PAIv. However, when applying the model to each specific natural forest region, the explanatory ability of the model increased clearly and can be up to 64.4%.

Our results highlighted a relationship between the basal area and volume increment of the oak stands. Basal area is an important indicator in forest management as it represents both the number and size of trees in the stand (Torres and Lovett, 2013). Theoretically, maximum volume increment is achieved at the optimal basal area and decreases with further basal area reduction (Pretzsch, 2010). However, the growth of mixed stands has often been reported to differ from monospecific stands. A study performed on mixed stands (Norway spruce *Picea abies* [L.] H.Karst.; silver fir *Abies alba* Mill.; and European beech) in Switzerland showed that overyielding was strongest at the highest basal area and decreased to under-yielding at the lowest basal area (Brunner and Forrester, 2020). Another study on the slopes of the northern Alborz Mount in Iran also reported similar results for mixed stands of uneven age. There was a positive relationship between volume increment with the basal area, and at the maximum basal areas, the largest volume increment was observed (Hamidi *et al.*, 2021). Cicsa *et al.* (2021) also demonstrated a similar relationship between volume and basal area of mixed Beech-Coniferous stands in the Romanian Carpathians. Our study areas are mixed forests where oak species predominate, so this can be explained by the influence of stand structure as well as competition between species. The relationship between basal area and volume increment provides the basis for sustainable forest management and predicts the volume of timber that can be harvested or thinned at each stage of the stands. This is particularly important to increase timber productivity and maintain the specific structure of the stand.

We indicated a significant effect of age on the volume increment of the stands. This is not surprising as the growth of trees is highly correlated with age. These mechanisms involve both the biomechanics and physiology of trees. Aging reduces photosynthesis, increases the cost of maintaining respiration and reduces the efficiency of water transport, leading to a reduction in growth rate (Johnson and Abrams, 2009; Groover, 2017; Marziliano *et al.*, 2019). Orwig *et al.* (2001) showed that *Quercus rubra* L. trees have a high growth rate at early age, which decreases after reaching a maximum. Study on three forest types mixed broad-leaf stands, mixed coniferous and coniferous-broadleaf mixed stands in China documented a similar relationship between age and volume increment (Yu *et al.*, 2017). Study in Germany also demonstrated a negative effect of age on PAIv (Stimm *et al.*, 2022). Our study is consistent with this trend. Establishing the relationship between age and volume increment of oak stands may help forest managers optimize the potential for timber production as well as improve the forest's carbon sequestration, contributing to climate change mitigation.

Tree height is an extremely crucial factor in forestry, as it is the basis for potential productivity and species selection. Our study noticed a proportional relationship between height and PAIv of oak stands. It is simple to accurately determine tree height through modern methods. In forestry practice, height is widely applied to develop models to predict productivity or volume increment of stands (Ryan and Yoder, 1997; Socha and Tymińska-Czabańska, 2019; Manso *et al.*, 2022). In addition, tree height is a sensitive to environmental changes (Vanclay, 1994; Pretzsch, 2010; Weiskittel *et al.*, 2011; West, 2014, 2015). Therefore, the relationship between tree height and PAIv in our study can provide an overview to predict the effects of climate and environmental change on changes in the volume and productivity of oak stands.

The results also proved the relationship between RSI and PAIv of oak stands. This was consistent with several other studies (Socha *et al.*, 2020; Viet *et al.*, 2023). Zhao *et al.* (2010) used relative spacing models to plan the thinning of the pine stands. Another study in South Africa also determined the maximum density by age of planted forests based on RSI (Gadow and Kotze, 2014). It is a useful indicator related to stand density which could help forest managers to determine appropriate thinning parameters taking into account the effect of thinning intensity on PAIv.

Besides the influence of stand characteristics on PAIv, we also found the effects of climate on PAIv of oak stands. We highlighted the effects of precipitation and temperature on volume increments of oak stands. The relationship between temperature, precipitation and volume increment of oak stands has been studied by many researchers (Pilcher and Gray, 1982; Drobyshev *et al.*, 2008; Di Filippo *et al.*, 2010; Caignard *et al.*, 2017; Xo Viet *et al.*, 2022). Drobyshev *et al.* (2008) documented that in the years when the climate was not so extreme, oak growth was primarily determined by the dynamics of summer precipitation. A study on oak stands in Central-West Germany found that the relationship between growth and precipitation is generally positive and opposite compared with temperature (Friedrichs *et al.*, 2009). Another study in central Italy and southern Sweden showed that temperature was negatively correlated with the growth of oak stands (Drobyshev *et al.*, 2008; Di Filippo *et al.*, 2010). These studies were similar to our results. Physiological responses of oaks to climate cause differences in growth rates. Despite that oak species are known to be thermophilic and drought-tolerant (Johnson *et al.*, 2002) overrun the optimal temperature may cause growth inhibition and even defoliation in oak trees. However, in some areas, it can be offset by precipitation, excessively high temperatures may limit the growth of oak stands (Gieger and Thomas, 2005; Browne *et al.*, 2019). Therefore, the rising temperatures and increasing frequency of droughts observed globally may have a significant impact on the growth patterns and even cause a change in the range of oak stands in the future.

Our study clarified the effect of slope and soil type on the PAIv of oak stands. We indicated a slight decrease in PAIv when the slope increases. The slope creates pressure on the wind and soil erosion, thereby affecting the growth of trees (Kravkaz-Kuscu *et al.*, 2018). Our results are in line with other studies. Rohner *et al.* (2013) noted that oak trees grew in diameter faster in areas with gentler slopes than in areas with steeper slopes. A study in Southern Portugal demonstrated that steep slopes reduce the productivity and size of oak trees. Their study also analyzed the effect of different soil types on oak growth (Costa *et al.*, 2008). Our results showed that the optimal soil for the growth of oak stands was black and gray land. The lowest PAIv was observed in oak stands grown on luvisols and podzols formed from light clayey sands and boulder clayey sands. Tymińska-Czabańska *et al.* (2021) also showed similar results, with the lowest productivity values observed in oak stands growing on gley-podzol soils suitable for coniferous sites. Different types of soil have quite different physical, chemical and biological properties, which have a significant effect on the growth of stands. In addition, soil structure is also related to the ability to absorb water, nutrients as well as root development, thereby affecting the growth of trees (Passioura, 1991). This result can help managers understand the relationship between volume increment, topography, and soil, thus indicating the optimal site conditions for the growth of this species. However, the selection of the optimum species should be conducted in comparison with the properties of alternative tree species. In the models developed for individual natural forest regions, the influence of site factors such as slope, climate on the PAIv of oak stands was insignificant in most regions. The lower importance of site factors is related to their high homogeneity in natural forest regions, which have been distinguished on the basis of the similarity of site conditions. For smaller areas like natural forest regions, PAIv was determined much more by stand characteristics. Site factors may be more important at larger spatial scales, where the variability of site conditions is larger.

The patterns observed between PAI and stand characteristics are important to determine the precise conditions for the optimal volume increment for oak stands. Our study was carried out on a large scale, which allowed us to consider a wide range of growth conditions for oak stands. The PAIv data allowed us to determine the relationship between individual variables and increment, but a certain limitation is the generalization associated with the five-year period. In order to determine the precise influence of individual variables, especially climatic ones, it is necessary to dispose of increment data with an annual resolution. However, such data are difficult to obtain and usually limited to a small spatial scale. Nevertheless, this should be a direction for further research. The precise determination of the influence of variables related to tree and site condition is consistent with the ideas of precision forestry and climate-smart forestry, which are particularly important to develop in the face of rapidly changing climate conditions.

Conclusions

We developed a GAM model that explains the influence of stand characteristics, climatic and topographic factors on PAIv of oak stands in Poland. Our results highlighted a strong relationship between the basal area and volume increment of the oak stands. As basal area increased, PAIv of oak stands increased significantly. We also identified a diminishing impact of age on PAIv. However, the rate of PAIv decline slowed when oak stand was over 100 years. Using RSI, we successfully demonstrated the relationship between stand density and PAIv. In the range of 20-35%, the slightest effect of RSI influence was seen. Additionally, our study noticed the slight effect of temperature and precipitation in shaping the volume increment of oak stands. Moreover, we documented the influence of soil type and topography on PAIv. For smaller areas such as natural forest regions, PAIv was mainly determined by stand characteristics, which was less influenced by site factors such as slope and climate. The establishment of these relationships within our study provides valuable information that can guide decision-making in oak stand management. This knowledge can also contribute to optimizing the potential for timber production while increasing the forest's capacity to sequester carbon, thereby contributing to climate change mitigation.

Authors' contribution

Conceptualization – H.D.X.V.; methodology – H.D.X.V., J.S., L.T.-C.; validation – H.D.X.V, S.K.; resources, J.S.; – data curation – J.S.; writing-original draft preparation – H.D.X.V, J.S., L.T.-C., S.K; writing-review and editing – H.D.X.V., J.S., L.T.-C.; visualization – H.D.X.V.; funding acquisition – J.S. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

Authors declare there is no conflict of interest.

Funding source and acknowledgement

This research was funded by General Directorate of State Forests in Poland under the project entitled: 'Modele przyrostu miąższości głównych gatunków lasotwórczych Polski' ('Volume increment models for the main forest-forming species of Poland'), contract no. EZ.271.3.20.2021.

References

Ábri, T., Rédei, K., 2022. Analyses of periodic annual increment by diameter and volume in differently aged black locust (*Robinia pseudoacacia* L.) stands: Case study. *Journal of Forest Science*, 68 (6): 213-219. DOI: https://doi.org/10.17221/25/2022-JFS.

Aertsen, W., Kint, V., van Orshoven, J., Özkan, K., Muys, B., 2010. Comparison and ranking of different modelling techniques for prediction of site index in Mediterranean mountain forests. *Ecological Modelling*, 221 (8): 1119-1130. DOI: https://doi.org/10.1016/j.ecolmodel.2010.01.007.

Albert, M., Nagel, R.V., Sutmöller, J., Schmidt, M., 2018. Quantifying the effect of persistent dryer climates on forest productivity and implications for forest planning: A case study in northern Germany. *Forest Ecosystems*, 5 (1): 1-21. DOI: https://doi.org/10.1186/S40663-018-0152-0.

Allen, M., Brunner, A., Antón-Fernández, C., Astrup, R., 2021. The relationship between volume increment and stand density in Norway spruce plantations. *Forestry: An International Journal of Forest Research*, 94 (1): 151-165. DOI: https://doi.org/10.1093/forestry/cpaa020.

Bauwe, A., Jurasinski, G., Scharnweber, T., Schröder, C., Lennartz, B., 2015. Impact of climate change on tree-ring growth of Scots pine, common beech and pedunculate oak in northeastern Germany. *iForest – Biogeosciences and Forestry*, 9 (1): 11. DOI: https://doi.org/10.3832/ifor1421-008.

Bayat, M., Bettinger, P., Hassani, M., Heidari, S., 2021. Ten-year estimation of Oriental beech (*Fagus orientalis* Lipsky) volume increment in natural forests: a comparison of an artificial neural networks model, multiple linear regression and actual increment. *Forestry: An International Journal of Forest Research*, 94 (4): 598-609. DOI: https://doi.org/10.1093/forestry/cpab001.

Browne, L., Wright, J.W., Fitz-Gibbon, S., Gugger, P.F., Sork, V.L., 2019. Adaptational lag to temperature in valley oak (*Quercus lobata*) can be mitigated by genome-informed assisted gene flow. *Proceedings of the National Academy of Sciences*, 116 (50): 25179-25185. DOI: https://doi.org/10.1073/pnas.1908771116.

Bruchwald, A., Rymer-Dudzińska T., Dudek, A., Michalak, K., Wróblewski, L., Zasada, M., 2000. Wzory empiryczne do określania wysokości i pierśnicowej liczby kształtu drzewa. (Empirical formulae for defining height and dbh shape figure of thick wood). *Sylwan*, 144 (10): 5-13.

Brunner, A., Forrester, D.I., 2020. Tree species mixture effects on stem growth vary with stand density – An analysis based on individual tree responses. *Forest Ecology and Management*, 473: 118334. DOI: https://doi.org/10.1016/j.foreco.2020.118334.

Budzyńska, K, Stuczyński, T., Zaliwski, A, 2001. Numerical agricultural soil map of Poland at the scale of 1:500 000. *Acta Agrophysica*, 50: 271-274.

Caignard, T., Kremer, A., Firmat, C., Nicolas, M., Venner, S., Delzon, S., 2017. Increasing spring temperatures favor oak seed production in temperate areas. *Scientific Reports*, 7 (1): 1-8. DOI: https://doi.org/10.1038/s41598-017-09172-7.

Cheng, J., Sun, J., Yao, K., Xu, M., Cao, Y., 2022. A variable selection method based on mutual information and variance inflation factor. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, 268: 120652. DOI: https://doi.org/10.1016/j.saa.2021.120652.

Cicsa, A., Tudoran, G.M., Boroeanu, M., Dobre, A.C., Spârchez, G., 2021. Estimation of the productivity potential of mountain sites (mixed beech-coniferous stands) in the Romanian Carpathians. *Forests*, 12 (5): 549. DOI: https://doi.org/10.3390/f12050549.

Coops, N.C., Shang, C., Wulder, M.A., White, J.C., Hermosilla, T., 2020. Change in forest condition: Characterizing non-stand replacing disturbances using time series satellite imagery. *Forest Ecology and Management*, 474: 118370. DOI: https://doi.org/10.1016/j.foreco.2020.118370.

Costa, A., Madeira, M., Oliveira, Â.C., 2008. The relationship between cork oak growth patterns and soil, slope and drainage in a cork oak woodland in Southern Portugal. *Forest Ecology and Management*, 255 (5-6): 1525-1535. DOI: https://doi.org/10.1016/j.foreco.2007.11.008.

Drobyshev, I., Niklasson, M., Eggertsson, O., Linderson, H., Sonesson, K., 2008. Influence of annual weather on growth of pedunculate oak in southern Sweden. *Annals of Forest Science*, 65 (5): 512-512. DOI: https://doi.org/10.1051/forest:2008033/metrics.

Eaton, E., Caudullo, G., Oliveira, S., Rigo, D. de, 2016. *Quercus robur* and *Quercus petraea* in Europe: Distribution, habitat, usage and threats. Luxembourg: Publication Office of the European Union. Available from: https://www.researchgate.net/publication/299471357_Quercus_robur_and_Quercus_petraea_in_Europe_distribution_habitat_usage_and_threats [accessed: 10.03.2023].

Di Filippo, A., Alessandrini, A., Biondi, F., Blasi, S., Portoghesi, L., Piovesan, G., 2010. Climate change and oak growth decline: Dendroecology and stand productivity of a Turkey oak (*Quercus cerris* L.) old stored coppice in Central Italy. *Annals of Forest Science*, 67 (7): 706. DOI: https://doi.org/10.1051/forest/2010031.

Fortin, M., Van Couwenberghe, R., Perez, V., Piedallu, C., 2019. Evidence of climate effects on the height-diameter relationships of tree species. *Annals of Forest Science*, 76 (1): 1-20. DOI: https://doi.org/10.1007/S13595-018-0784-9.

Friedrichs, D.A., Bntgen, U., Frank, D.C., Esper, J., Neuwirth, B., Loffler, J., 2009. Complex climate controls on 20th century oak growth in Central-West Germany. *Tree Physiology*, 29 (1): 39-51. DOI: https://doi.org/10.1093/treephys/tpn003.

Gadow, K.V., Kotze, H., 2014. Tree survival and maximum density of planted forests – Observations from South African spacing studies. *Forest Ecosystems*, 1 (1): 1-9. DOI: https://doi.org/10.1186/S40663-014-0021-4.

Gasparini, P., Di Cosmo, L., Rizzo, M., Giuliani, D., 2017. A stand-level model derived from National Forest Inventory data to predict periodic annual volume increment of forests in Italy. *Journal of Forest Research*, 22 (4): 209-217. DOI: https://doi.org/10.1080/13416979.2017.1337260.

Gauthier, S., Bernier, P., Kuuluvainen, T., Shvidenko, A.Z., Schepaschenko, D.G., 2015. Boreal forest health and global change. *Science*, 349 (6250): 819-822. DOI: https://doi.org/10.1126/SCIENCE.AAA9092.

Gieger, T., Thomas, F.M., 2005. Differential response of two Central-European oak species to single and combined stress factors. *Trees – Structure and Function*, 19 (5): 607-618. DOI: https://doi.org/10.1007/S00468-005-0424-5.

Greenwell, B.M., Boehmke, B.C., 2020. Variable importance plots-an introduction to the vip package. *The R Journal*, 12 (1): 343-366. Available from: https://journal.r-project.org/archive/2020/RJ-2020-013/RJ-2020-013.pdf [accessed: 17.03.2022].

Groover, A., 2017. Age-related changes in tree growth and physiology. *Encyclopedia of Life Sciences*, 12 (1): 1-7. DOI: https://doi.org/10.1002/9780470015902.a0023924.

Hamidi, S.K., Zenner, E.K., Bayat, M., Fallah, A., 2021. Analysis of plot-level volume increment models developed from machine learning methods applied to an uneven-aged mixed forest. *Annals of Forest Science*, 78 (1): 1-16. DOI: https://doi.org/10.1007/S13595-020-01011-6.

Hastie, T.J., Tibshirani, R.J., 2017. Generalized additive models. Chapman and Hall/CRC. DOI: https://doi.org/10.1201/9780203753781.

James, G., Witten, D., Hastie, T., Tibshirani, R., 2013. An introduction to statistical learning. In: Springer texts in statistics. New York: Springer, pp. 1-14. DOI: https://doi.org/10.1007/978-1-4614-7138-7.

Johnson, P.S., Shifley, S.R., Rogers, R., 2002. The ecology and silviculture of Oaks. Oxford University Press, 544 pp. Available from: www.cabi-publishing.org [accessed: 12.04.2023].

Johnson, S.E., Abrams, M.D., 2009. Age class, longevity and growth rate relationships: Protracted growth increases in old trees in the eastern United States. *Tree Physiology*, 29 (11): 1317-1328. DOI: https://doi.org/10.1093/treephys/tpp068.

Kravkaz-Kuscu, I.S., Sariyildiz, T., Cetin, M., Yigit, N., Sevik, H., Savaci, G., 2018. Evaluation of the soil properties and primary forest tree species in Taskopru (Kastamonu) district. *Fresenius Environmental Bulletin*, 27 (3): 1613-1617.

Krug, J.H.A., 2019. How can forest management increase biomass accumulation and CO2 sequestration? A case study on beech forests in Hesse, Germany. *Carbon Balance and Management*, 14 (1): 1-16. DOI: https://doi.org/10.1186/S13021-019-0132-X/TABLES/5.

Larsen, K., 2015. GAM: The predictive modeling silver bullet. *Public*. Available from: https://multithreaded.stitchfix.com/blog/2015/07/30/gam/ [accessed: 05.03.2023].

Manso, R., Davidson, R., Mclean, J.P., 2022. Diameter, height and volume increment single tree models for improved Sitka spruce in Great Britain. *Forestry: An International Journal of Forest Research Forestry*, 95 (3): 391-404. DOI: https://doi.org/10.1093/foresj/cpab049.

Marziliano, P.A., Tognetti, R., Lombardi, F., 2019. Is tree age or tree size reducing height increment in *Abies alba* Mill. at its southernmost distribution limit? *Annals of Forest Science*, 76 (1): 1-12. DOI: https://doi.org/10.1007/S13595-019-0803-5.

Melnychuk, M.C., Peterson, E., Elliott, M., Hilborn, R., 2017. Fisheries management impacts on target species status. *Proceedings of the National Academy of Sciences of the United States of America*, 114 (1): 178-183. DOI: https://doi.org/10.1073/pnas.1609915114.

Mendes, H., De Fátima Borges, M., Scott, C.L., Frid, C., 2008. Climatic impact on hake recruitment in Iberian Peninsula and implications for fisheries management: An InExFish project study. Halifax: Annual Science Conference. Available from: https://www.ices.dk/sites/pub/CM%20Doccuments/CM-2008/L/L2608.pdf [accessed: 23.05.2023].

Meredieu, C., Perret, S., Dreyfus, P., 2002. Modelling dominant height growth: Effect of stand density. Workshop on Reality models and parameters estimation: The forestry scenario, Sesimbra, PRT, 2-5 June 2002, pp. 111-121. Available from: https://hal.inrae.fr/hal-02581462 [accessed: 23.11.2022].

Murray, L., Nguyen, H., Lee, Y.-F., Remmenga, M.D., Smith, D.W., 2012. Variance inflation factors in regression models with dummy variables. In: W. Song, ed. Conference on Applied Statistics in Agriculture. Kansas State University Libraries, New Prairie Press, pp. 161-177. DOI: https://doi.org/10.4148/2475-7772.1034.

Orwig, D.A., Cogbill, C.V, Foster, D.R., O'keefe, J.F., 2001. Variations in old-growth structure and definitions: Forest dynamics on Wachusett mountain, Massachusetts. *Ecological Applications*, 11 (2): 437-452. DOI: https://doi.org/10.1890/1051-0761.

Passioura, J.B., 1991. Soil structure and plant growth. *Australian Journal of Soil Research*, 29 (6): 717-728. DOI: https://doi.org/10.1071/SR9910717.

Petritan, A.M., Biris, I.A., Merce, O., Turcu, D.O., Petritan, I.C., 2012. Structure and diversity of a natural temperate sessile oak (*Quercus petraea* L.) – European Beech (*Fagus sylvatica* L.) forest. *Forest Ecology and Management*, 280: 140-149. DOI: https://doi.org/10.1016/j.foreco.2012.06.007.

Pilcher, J.R., Gray, B., 1982. The relationships between Oak tree growth and climate in Britain. *The Journal of Ecology*, 70 (1): 297. DOI: https://doi.org/10.2307/2259880.

Pretzsch, H., 2010. Forest dynamics, growth and yield: From measurement to model. Berlin, Heidelberg: Springer, 664 pp. DOI: https://doi.org/10.1007/978-3-540-88307-4.

R Core Team, 2021. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Available from: https://www.R-project.org/.

Río, M., Sterba, H., 2009. Comparing volume growth in pure and mixed stands of *Pinus sylvestris* and *Quercus pyrenaica*. *Annals of Forest Science*, 66 (5): 502-502. DOI: https://doi.org/10.1051/forest/2009035.

Rohner, B., Bugmann, H., Bigler, C., 2013. Estimating the age-diameter relationship of oak species in Switzerland using nonlinear mixed-effects models. *European Journal of Forest Research*, 132 (5-6): 751-764. DOI: https://doi.org/10.1007/S10342-013-0710-5.

Ryan, M.G., Yoder, B.J., 1997. Hydraulic limits to tree height and tree growth: What keeps trees from growing beyond a certain height? *BioScience*, 47 (4): 235-242. DOI: https://doi.org/10.2307/1313077/2/47-4-235.

Socha, J., Hawryło, P., Pierzchalski, M., Stereńczak, K., Krok, G., Wężyk, P., Tymińska-Czabańska, L., 2020. An allometric area-based approach – A cost-effective method for stand volume estimation based on ALS and NFI data. *Forestry: An International Journal of Forest Research*, 93 (3): 344-358. DOI: https://doi.org/10.1093/forestry/cpz062.

Socha, J., Tymińska-Czabańska, L., 2019. A method for the development of dynamic site index models using height – Age data from temporal sample plots. *Forests*, 10 (7): 542. DOI: https://doi.org/10.3390/f10070542.

Stimm, K., Heym, M., Nagel, R.V., Uhl, E., Pretzsch, H., 2022. Long-term productivity of monospecific and mixed Oak (*Quercus petraea* [Matt.] Liebl. and *Quercus robur* L.) Stands in Germany: Growth dynamics and the effect of stand structure. *Forests*, 13 (5): 724. DOI: https://doi.org/10.3390/F13050724/S1.

Stokland, J.N., 2021. Volume increment and carbon dynamics in boreal forest when extending the rotation length towards biologically old stands. *Forest Ecology and Management*, 488: 119017. DOI: https://doi.org/10.1016/J.FORECO.2021.119017.

Tomter, S.M., Kuliešis, A., Gschwantner, T., 2016. Annual volume increment of the European forests – description and evaluation of the national methods used. *Annals of Forest Science*, 73 (4): 849-856. DOI: https://doi.org/10.1007/S13595-016-0557-2.

Torres, A.B., Lovett, J.C., 2013. Using basal area to estimate aboveground carbon stocks in forests: La Primavera Biosphere's Reserve, Mexico. *Forestry: An International Journal of Forest Research*, 86 (2): 267-281. DOI: https://doi.org/10.1093/FORESTRY/CPS084.

Trouillier, M., van der Maaten-Theunissen, M., Scharnweber, T., Wilmking, M., 2020. A unifying concept for growth trends of trees and forests – The 'Potential Natural Forest'. *Frontiers in Forests and Global Change*, 3: 581334. DOI: https://doi.org/10.3389/FFGC.2020.581334.

Tymińska-Czabańska, L., Socha, J., Maj, M., Cywicka, D., Hoang Duong, X.V., 2021. Environmental drivers and age trends in site productivity for oak in southern Poland. *Forests*, 12 (2): 209. DOI: https://doi.org/10.3390/f12020209.

Vanclay, J.K., 1994. Modelling forest growth and yield: applications to mixed tropical forests. Wallingford: CAB International, 312 pp.

Viet, H.D.X., Tymińska-Czabańska, L., Socha, J., 2023. Modeling the effect of stand characteristics on Oak volume increment in Poland using generalized additive models. *Forests*, 14 (1): 123. DOI: https://doi.org/10.3390/f14010123.

Vospernik, S., Heym, M., Pretzsch, H., Pach, M., Steckel, M., Aldea, J., Brazaitis, G., Bravo-Oviedo, A., Del Rio, M., Löf, M., Pardos, M., Bielak, K., Bravo, F., Coll, L., Černý, J., Droessler, L., Ehbrecht, M., Jansons, A., Korboulewsky, N., Jourdan, M., Nord-Larsen, T., Nothdurft, A., Ruiz-Peinado, R., Ponette, Q., Sitko, R., Svoboda, M., Wolff, B., 2023. Tree species growth response to climate in mixtures of *Quercus robur/Quercus petraea* and *Pinus sylvestris* across Europe – a dynamic, sensitive equilibrium. *Forest Ecology and Management*, 530: 120753. DOI: https://doi.org/10.1016/j.foreco.2022.120753.

Wang, W., Chen, X., Zeng, W., Wang, J., Meng, J., 2019. Development of a mixed-effects individual-tree basal area increment model for Oaks (*Quercus* spp.) considering forest structural diversity. *Forests*, 10 (6): 474. DOI: https://doi.org/10.3390/F10060474.

Weiskittel, A.R., Hann, D.W., Kershaw, J.A., Vanclay, J.K., 2011. Forest growth and yield modeling. John Wiley & Sons, Ltd., 45 pp. DOI: https://doi.org/10.1002/9781119998518.

West, P.W., 2014. Growing plantation forests. Springer International Publishing, 329 pp. DOI: https://doi.org/10.1007/978-3-319-01827-0.

West, P.W., 2015. Tree and forest measurement. Springer International Publishing, 209 pp. DOI: https://doi.org/10.1007/978-3-319-14708-6.

Wood, S.N., 2017. Generalized additive models. New York: Chapman and Hall/CRC, 496 pp. DOI: https://doi.org/10.1201/9781315370279.

Wu, S.-H., Chao, C.-T., Huang, B.-H., Luo, M.-X., Duan, X.-G., Liao, P.-C., 2020. Environmental disturbance in natural forest and the effect of afforestation methods on timber volume increment in *Pinus sylvestris* L. var. *mongolica* Litv. *Global Ecology and Conservation*, 24: 1311. DOI: https://doi.org/10.1016/j.gecco.2020.e01311.

Xo Viet, H.D., Tymińska-Czabańska, L., Socha, J., 2022. Drivers of site productivity for oak in Poland. *Dendrobiology*, 88: 81-93. DOI: https://doi.org/10.12657/denbio.088.006.

Yu, Y., Chen, J.M., Yang, X., Fan, W., Li, M., He, L., 2017. Influence of site index on the relationship between forest net primary productivity and stand age. *PlosOne*, 12 (5): 177084. DOI: https://doi.org/10.1371/journal.pone.0177084.

Zacharski, R., 2018. Training Sets, Test Sets, and 10-fold Cross-validation. KDnuggets. Available from: https://www.kdnuggets.com/2018/01/training-test-sets-cross-validation.html [accessed: 30.12.2022].

Zhao, D., Kane, M., Borders, B.E., 2010. Development and applications of the relative spacing model for loblolly pine plantations. *Forest Ecology and Management*, 259 (10): 1922-1929. DOI: https://doi.org/10.1016/j.foreco.2010.02.003.

Zielony, R., Kliczkowska, A., 2012. Regionalizacja przyrodniczo-leśna Polski 2010. Warszawa: Centrum Informacyjne Lasów Państwowych, 359 pp.

STRESZCZENIE

Wpływ cech drzewostanu i czynników środowiskowych na przyrost miąższości dębu w Polsce

Informacja o przyroście drzewostanów jest potrzebna do zrównoważonego i efektywnego zarządzania zasobami leśnymi. Przyrost miąższości stanowi cenny wskaźnik rozwoju drzewostanów i może służyć jako wskaźnik zmiany warunków wzrostu. Dane dotyczące zmiany przyrostu miąższości mogą dostarczyć istotnych informacji na temat kondycji lasu oraz wpływu różnych czynników na jego rozwój. Informacja o przyroście miąższości ma również istotne znaczenie w monitorowaniu reakcji drzewostanów na zmiany środowiskowe, ułatwiając wczesne wykrywanie potencjalnych zagrożeń i polepszając zrozumienie dynamiki ekosystemów leśnych. Z przyrostem miąższości związana jest bezpośrednio również ilość biomasy produkowanej przez drzewostan, dlatego przyrost miąższości stanowi podstawę do ilościowego ustalania ilości węgla magazynowanego w ekosystemach leśnych. Określanie przyrostu miąższości ma więc kluczowe znaczenie dla prognozowania przyszłej podaży drewna, zrozumienia potencjału sekwestracji węgla w lasach, planowania etatów cięć i optymalizacji wieku rębności dla różnych gatunków drzew i strategii zarządzania. Modele wzrostu i produkcyjności drzewostanów stanowią niezbędne narzędzia w gospodarce leśnej. Wykorzystując do modelowania przyrostu miąższości drzewostanów zmienne siedliskowe, można umożliwić ocenę długoterminowego oddziaływania czynników klimatycznych i środowiskowych na przyrost drzewostanów.

Celem niniejszego badania było opracowanie modeli opisujących zależność przyrostu miąższości drzewostanów dębowych od cech drzewostanu i czynników środowiskowych. W analizach wykorzystano uogólnione modele addytywne (GAM – *generalised additive models*), które pozwalają na modelowanie skomplikowanych wzorców występujących w danych, w tym interakcji między zmiennymi czy nieliniowych trendów w badanych zależnościach. Modele te uwzględniają nieliniowe relacje między zmiennymi objaśniającymi a zmienną zależną oraz pozwalają na wykorzystanie w modelowaniu wielu zmiennych objaśniających i dużej liczby obserwacji. Korzystając z GAM, można analizować wpływ każdej indywidualnej zmiennej na zmienną zależną, utrzymując inne zmienne na stałym poziomie. GAM zapewnia również możliwość kontrolowania wygładzania funkcji predykcyjnych w celu zmniejszenia nadmiernego dopasowania. W niniejszym badaniu wykorzystano dane z lat 2005-2019 z wielkoobszarowej inwentaryzacji stanu lasów (WISL) w Polsce. Zebrano dane pochodzące z 1945 powierzchni próbnych zlokalizowanych w drzewostanach, w których gatunkami dominującymi były dęby *Quercus petraea* (Matt.) Liebl. i *Quercus robur* L. (ryc. 1). Do modelowania wykorzystano również dane opisujące cechy środowiskowe (topografia, gleby, klimat). Takie połączenie danych WISL opisujących charakterystykę drzewostanów i danych siedliskowych pozwoliło na opracowanie odpowiednich modeli opisujących wpływ cech drzewostanu oraz czynników klimatycznych i topograficznych na okresowy przyrost miąższości (PAIv – *periodic annual volume increment*) drzewostanów dębowych

w Polsce (tab. 1-5). Wyniki badań wskazują, że wiek i powierzchnia pierśnicowego przekroju drzewostanów najmocniej wpływały na okresowy przyrost miąższości drzewostanów dębowych (ryc. 2). PAIv wzrastał o około 3 m^3/ha/rok na każde 10 m^2/ha wzrostu powierzchni przekroju pierśnicowego (ryc. 3a) i zmniejszał się znacząco wraz ze wzrostem wieku drzewostanów dębowych (ryc. 3b). Na przyrost miąższości drzewostanów dębowych wpływały również wysokość górna drzewostanów (ryc. 3c) i wskaźnik opisujący zagęszczenie drzewostanów (RSI – *relative spacing index*) (ryc. 3d). Ponadto w badaniach odnotowano niewielki wpływ średniej sumy opadów w najsuchszym kwartale (ryc. 4a), średniej sumy opadów w najcieplejszym kwartale (ryc. 4b) i średniej temperatury w najwilgotniejszym kwartale (ryc. 4c) na okresowy przyrost miąższości drzewostanów dębowych. W badaniu przeanalizowano również związek między PAIv a topografią i typem gleby. PAIv miał tendencję do zmniejszania się, gdy nachylenie terenu przekraczało 5 stopni (ryc. 5a). W drzewostanach na glebach charakteryzujących się wysokim poziomem żyzności zaobserwowano najwyższy przyrost (ryc. 5b). Opracowany model GAM wyjaśnia 43,8% (R^2_{adj}) zmienności obserwowanej PAIv (tab. 6 i 7). R^2_{adj} został obliczony na podstawie 10-krotnej walidacji krzyżowej. Opracowany model nie wykazywał nadmiernego dopasowania (ryc. 6). Zastosowanie modelu GAM do poszczególnych krain przyrodniczo-leśnych znacząco poprawiło zdolność wyjaśniającą modelu, która osiągnęła nawet 64,4% (R^2_{adj}) (tab. 8). Oznacza to, że duży wpływ na okresowy przyrost miąższości drzewostanów dębowych w Polsce wywierają regionalne czynniki siedliskowe.