Rozprawa doktorska

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Effect of stand density and site conditions on growth and productivity of oak in Poland

Wpływ zagęszczenia drzewostanu i warunków siedliskowych na wzrost i produkcyjność dębu w Polsce

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Summary

Forest growth and site productivity are critical to forest management. This information allows forest managers to predict stand growth rates and monitor the response of stands to environmental changes, which are key to making effective forest management decisions. In forestry practice, forest growth and site productivity are often determined using models that allow tree and stand growth to be simulated for different climate change scenarios or management strategies, enabling stakeholders to assess the long-term effects of environmental factors on the stand. The aim of this study was to develop models to describe the relationship of volume increment of oak stands and site productivity for oak as a function of stand characteristics and environmental factors. In order to ensure full representation of site factors across Poland, the study used data from the National Forest Inventory in Poland collected in 2005-2019. The effect of stand characteristics and site variables on site productivity and volume increment of oak stands was analysed using generalised additive models (GAM). Modelling results showed that site productivity for oak, as measured by the site index, was strongly dependent on environmental variables, stand age and density. Site productivity for oak was also affected by climatic factors, soil type, geology and height above sea level. In turn, volume increment of oak in Poland was significantly determined by stand characteristics such as basal area, age, top height and relative stand density index. The study also showed the effect of temperature, precipitation, slope and soil subtype on volume increment. In more homogeneous areas, such as natural forest regions, volume increment was mainly determined by stand characteristics and to a lesser extent by site factors such as slope and climate. The study provided information that can help inform management decisions for oak stands. This knowledge can also be used to optimise the potential for timber production, while increasing the forest's capacity to sequester carbon, thereby contributing to climate change mitigation.

Keywords: Site productivity, site index, forest growth, volume increment, GAM.

Streszczenie

Wzrostu lasów i produkcyjność siedlisk mają kluczowe znaczenie dla gospodarki leśnej. Informacje te pozwalają zarządcom lasów przewidywać tempo wzrostu drzewostanów i monitorować reakcję drzewostanów na zmiany środowiskowe, które są kluczowe dla podejmowania skutecznych decyzji w zakresie zarządzania zasobami leśnymi. W praktyce leśnej wzrost lasu i produkcyjność siedlisk są często określane przy użyciu modeli, które pozwalają symulować wzrost drzew i drzewostanów dla różnych scenariuszy zmian klimatycznych lub strategii zarządzania, umożliwiając zainteresowanym stronom ocenę długoterminowego wpływu czynników środowiskowych na drzewostan. Celem pracy było opracowanie modeli opisujących zależność przyrostu miąższości drzewostanów dębowych i produkcyjności siedlisk dla dębu w zależności od cech drzewostanu i czynników środowiskowych. W celu zapewnienia pełnej reprezentacji czynników siedliskowych na całym terytorium Polski w badaniach wykorzystano Dane z Wielkoobszarowej Inwentaryzacji Stanu Lasu w Polsce zebrane w latach 2005-2019. Wpływ cech drzewostanów i zmiennych siedliskowych na produkcyjność siedliska oraz przyrost miąższości drzewostanów dębowych analizowano za pomocą uogólnionych modeli addytywnych (GAM). Wyniki modelowania wykazały, że produkcyjność siedliska dla dębu, mierzona wskaźnikiem bonitacji, była silnie uzależniona od zmiennych środowiskowych, wieku drzewostanu i zagęszczenia. Na produkcyjność siedliska dla dębu miały również wpływ czynniki klimatyczne, rodzaj gleby, geologia i wysokość nad poziomem morza. Z kolei przyrost miąższości dębu w Polsce był istotnie determinowany przez cechy drzewostanu, takie jak powierzchnia pierśnicowego przekroju, wiek, wysokość górna i względny wskaźnik zagęszczenia. W badaniach wykazano również wpływ temperatury, opadów, nachylenia terenu i podtypu gleby na przyrost miąższości. Na bardziej homogenicznych obszarach, takich jak krainy przyrodniczo-leśne, przyrost miąższości był przede wszystkim determinowany przez cechy drzewostanu, a w mniejszym stopniu przez czynniki siedliskowe, takie jak nachylenie terenu i klimat. Badania dostarczyły informacji, które mogą być pomocne w podejmowaniu decyzji dotyczących gospodarowania drzewostanami dębowym. Wiedza ta może być również wykorzystana do optymalizacji potencjału produkcji drewna, przy jednoczesnym zwiększeniu zdolności lasu do sekwestracji dwutlenku węgla, przyczyniając się tym samym do łagodzenia zmian klimatycznych.

Słowa kluczowe: Produkcyjność siedlisk, wskaźnik bonitacji, wzrost lasu, przyrost miąższości, GAM

Table of contents

1. List of publications

The thesis is prepared as a collection of articles published in scientific journals under the following topics:

Publication 1

Viet, H. D. X., Tymińska-Czabańska, L., Socha, J. (2022). Drivers of site productivity for oak in Poland. Dendrobiology, 88, 81–93.

https://doi.org/10.12657/denbio.088.006

(MEiN list 100 pts., IF 1.0); Authors contributions (VHDX – 80%, LTC-10%, JS-10%).

Publication 2

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.

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(MEiN list 100 pts., IF 3.0); Authors contributions (VHDX – 80%, LTC-10%, JS-10%).

Publication 3

Viet, H. D. X., Tymińska-Czabańska, L., Konopa, S., Socha, J. (2024). Effect of stand characteristics and environmental factors on the volume increment of Oak in Poland, Sylwan, 168 (2).

(MEiN list 70 pts., IF 0.7); Authors contributions (VHDX – 75%, LTC-5%, SK-5%, JS-15%).

2. Introduction

Understanding forest growth and site productivity is critical to forest research and management. Forest site productivity is the production that can be realized at a particular site with a given species and a specified management regime. It depends on natural factors inherent to the site and management-related factors (Skovsgaard & Vanclay, 2008a). Forest site productivity is closely related to wood production and the amount of carbon stored in the forest ecosystem (West, 2015). Information on site productivity can also provide valuable insights into stand response to environmental changes and early detection of potential pest and disease risks (Coops et al., 2020; Gauthier et al., 2015; Wu et al., 2020). Therefore, accurate estimate of forest productivity is essential for selecting silvicultural treatments and planning sustainable forest management.

In forestry practices, the most common measure of site productivity is the site index (SI), estimated from stand height at a given base age for a specific species (Joan DeYoung, 2016; Sugawara & Nikaido, 2014). It is mainly determined using phytocentric methods (Hägglund B, 1981; Skovsgaard & Vanclay, 2008b). However, phytocentric methods are only suitable for even-aged, monoculture and undisturbed stands (Carmean & Lenthall, 1989; Fu et al., 2018; Huang & Titus, 1993; Pokharel & Dech, 2011; Skovsgaard & Vanclay, 2008b; Socha, Hawryło, et al., 2020; West, 2015). In uneven-aged forests, height growth inhibition may occur at an early age. Therefore, determining SI through tree height may not be accurate, making the phytocentric method restricted for uneven-aged stands (Aertsen et al., 2011; Barrett, 1978; Bettinger et al., 2017; Brüllhardt et al., 2020; McQuilkin, 1975). Phytocentic methods may also be inappropriate for mixed or young stands (Dănescu et al., 2017; Jaworski A, 2014; Ważyński B, 1967). In addition, phytocentric methods limit the ability to identify individual biological determinants of growth or prediction from environmental variables. Importantly it is also impossible to determine site productivity using phytocentric methods for non-forest areas (Skovsgaard & Vanclay, 2008a; Vanclay, 1994). To solve these problems, geocentric methods are used for modeling site productivity. Geocentric methods are based on determining the influence of environmental features to estimate forest productivity (Skovsgaard & Vanclay, 2008a; West, 2014, 2015). The advantage of geocentric methods is that they provide a more dynamic representation of site conditions by considering the impact of factors on current and past growth (Bontemps & Bouriaud, 2014; Dănescu et al., 2017). Moreover, geocentric methods allows for continuous mapping of SI across the landscape and direct predictions based on environmental variables (Skovsgaard & Vanclay, 2008a).

Because forestry is often concerned with the amount of timber that can be harvested, managers can use indices representing volume production to evaluate site productivity (Skovsgaard & Vanclay, 2008a). Volume increment is a valuable indicator of stand performance and growth over time (Vanclay, 1994). Numerous studies have consistently shown a relationship between volume and productivity (Ábri & Rédei, 2022a; Bayat et al., 2021; Gasparini et al., 2017; Tomter et al., 2016; Wang et al., 2019). Today, data from the National Forest Inventory (NFI) can provide accurate and specific information on the various components of the annual increment (Tomter et al., 2016). Instead of annual measurements, periodic surveys are performed at n-year intervals. The recorded increment in diameter, height and volume must be divided by n, referred to as the periodic annual increment (Pretzsch, 2009). Periodic annual increment is a more realistic representation of the ability of a tree (or stand) to grow to a given age or size (Ábri & Rédei, 2022a). Periodic volume change is the basis of many forest growth and productivity models (Ábri & Rédei, 2022a; Bayat et al., 2021; Gasparini et al., 2017; Kaźmierczak, 2013; Tomter et al., 2016; Wang et al., 2019) and is essential for determining sustainable harvests in uneven-aged forest management (Bayat et al., 2013; Hamidi et al., 2021).

Forest growth and productivity models often use regression analyses to estimate how a dependent variable responds to changes in its relationship with the independent variables (Weiskittel et al., 2011). However, these analyses may have limitations due to the complex relationship between the dependent and independent variables or the mutual interaction between independent variables (Hamidi et al., 2021; Leite et al., 2020). Because of strong linear correlations between independent variables, regression models may lose their reliability. In addition, regression models cannot automatically handle nonlinearities (Harrell, 2015). Among the many available modeling methods, Aertsen et al. (2010) highlighted the suitability of the generalised additive model (GAM). By substituting nonparametric functions for the linear function of the explanatory variable, GAM allows estimates to be made for multivariate variables using the additive approximation of the regression function. GAM provides a model that can be interpreted for non-linear data. When the number of available predictors is large, GAM can model highly complex nonlinear relationships. Using GAM, analyse of each variable's effect on a dependent variable while holding all other variables fixed is possible. GAM also provides the ability to control the smoothing of the prediction functions to reduce over-fitting. In addition, by controlling the swings of the prediction functions, it is possible to maintain the trade-off between bias and variance (Hastie & Tibshirani, 2017; Wood, 2017).

Oak forests are recognized as one of the most critical forest types in Europe (Vospernik et al., 2023). Oaks play an important role in maintaining the habitat of many wildlife species, biodiversity and landscape aesthetics. Economically, oak wood has high strength and resistance, so it is widely used in construction, furniture making, and wooden floors (Schroeder et al., 2021). Despite its important ecological and economic role in forestry, previous studies on oak productivity have been relatively localized and focused on small-scale forestry (Bijak & Sacewicz, 2018; Dobrowolska, 2008; Graney, 1977; Nunes et al., 2015; Tymińska-Czabańska et al., 2021). In recent decades, ongoing changes in central European site conditions may have favoured oaks over conifers (Dyderski et al., 2018; Hanewinkel et al., 2012a). Therefore, developing national-scale geocentric models for oak can partially fill this knowledge gap and improve our understanding of the influences of various environmental factors on site productivity for this major forest-forming tree species.

3. Reasons for choosing research topic

Growth and productivity models are valuable tools for understanding the dynamics of forest ecosystems. These models help us to understand how forests grow and change over time and how they respond to different environmental conditions (Bontemps & Bouriaud, 2014; Vanclay, 1994). Modeling site productivity and stand growth allows us to predict future stand changes under the influence of environmental factors and silvicultural practices, thereby proposing appropriate solutions for forest management and development. For this reason, research to develop forest growth and productivity models is vital in forestry.

Forest growth is influenced by stand characteristics (Joan DeYoung, 2016; Li et al., 2020) and a various of environmental factors, such as soil characteristics (Costa et al., 2008; Kravkaz-Kuscu et al., 2018; Passioura, 1991; Pietrzykowski et al., 2015), climate (Dyderski et al., 2018; Hanewinkel et al., 2012b; Pilcher & Gray, 1982; Salas-Eljatib, 2021), silvicultural techniques (Attocchi, 2015; Bose et al., 2018; Mäkinen & Isomäki, 2004; Neumann & Hasenauer, 2021). In forestry practice, information on site index and volume increment can be integrated with stand characteristics or other environmental factors to developed geocentric models (Berrill & O'Hara, 2014; Monserud et al., 2011; Seynave et al., 2005; Sharma & Parton, 2018, 2019). These models can clarify the effects of various biological, management, and environmental factors on forest dynamics (Hemingway &

Kimsey, 2020). In addition, models may predict future forest productivity under different management or climate change scenarios as well as simulate the long-term and large-scale response of forests to changing environmental conditions (Bengtsson et al., 2000; Charru et al., 2017; Dyderski et al., 2018; Mirhashemi et al., 2023; Peng, 2000). Knowledge of growth and productivity models is essential for assessing risk, selecting silvicultural treatments, and making appropriate forest management decisions to increase the adaptive capacity and resilience of forests to climate change (de la Fuente et al., 2018; Seely et al., 2015; Sugawara & Nikaido, 2014).

In recent decades, the development of statistical models to explain the dependence of site productivity on environmental variables at different spatial scales has become very popular (Bontemps & Bouriaud, 2014; Brandl et al., 2018; Nothdurft et al., 2012). Previously, forest productivity studies were limited to small scales due to data limitations. However, information about geography and climate has become more accessible with the development of science and the availability of remote sensing data (Fiandino et al., 2020; Parresol et al., 2017). Many large-scale studies have been conducted based on NFI data. The NFI provides accurate information on the area, distribution, composition and condition of forests (Brandl et al., 2018). Combining data from different inventories is the basis for assessing growth and predicting future forest productivity. Numerous methods for modeling forest growth and productivity have been explored over the years. One approach that has been increasingly in use over the years is the GAM model (Aertsen et al., 2010; Tymińska-Czabańska et al., 2021). Due to its ability to model complex non-linear relationships when the number of potential predictors is large, GAM can use extensive NFI datasets as well as topographic, climate variables from different data sources to describe site productivity relationships (Bontemps & Bouriaud, 2014; de Wergifosse et al., 2022; Sharma et al., 2015; Sharma & Parton, 2018, 2019). Thus, studying the factors influencing the site productivity of oak is vital from both a practical and scientific perspective.

4. Objectives of the thesis

The main objective of this thesis was to analyze the effects of stand characteristics and site conditions on the site productivity of oak. A second aim of the study was the develop of geocentric models that describe the relationship between the periodic annual volume increment of oak with stand characteristics and environmental factors.

The main assumptions of the thesis are:

1. The use of available GIS data characterising environmental conditions (topography, geology, soils, climate) combined with data on stand characteristics allows the development of appropriate site productivity models.

2. Site conditions affect the relationship between volume increment and stand characteristics, so their use in modelling will improve the accuracy of volume increment models for oak.

3. Observed changes in site conditions lead to changes in site productivity for oak.

Detailed objectives have been implemented to achieve the overall objective:

1. Identify significant environmental variables and stand characteristics that influence the site productivity for oak (**Publication 1**).

2. Development of a model describing site productivity as a function of stand and site characteristics (**Publication 1**).

3. Development of a model for the prediction of periodic annual volume increment as a function of stand characteristics (**Publication 2**).

4. Identify the stand characteristics and environmental factors that significantly affect oak volume increment (**Publication 3**).

5. Development of regional models of periodic annual volume increment for oak (**Publication 3**).

5. Materials and Methods

a. Materials

The materials used for this thesis were measurement data of NFI activities in Poland from 2005 to 2019. The measurement period started in 2005, and each measurement cycle was five years long. The data covered three periods (the first was 2005-2009, the next was 2010-2014, and the third was 2014-2019) and were collected from sample plots in stands with dominant oak species (*Quercus sessilis* and *Quercus robur*). 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 so we did not separate the two oak species in this thesis. NFI measurements are taken on permanent sample plots located in 4 × 4km grid. Measurements were made on two types of concentric circular sample plots of appropriate sizes for the inventory characteristics (Talarczyk, 2014). The number of sample plots varied in each publication.

In publication 1, the study materials were collected from 2490 sample plots (Fig. 1). The sample plots were established in oak stands with ages varying from 9 to 210 years, and the number of trees per hectare ranged from 20 to 2850. The average diameter of oak is 31.49cm, and the average height is 21.36cm.

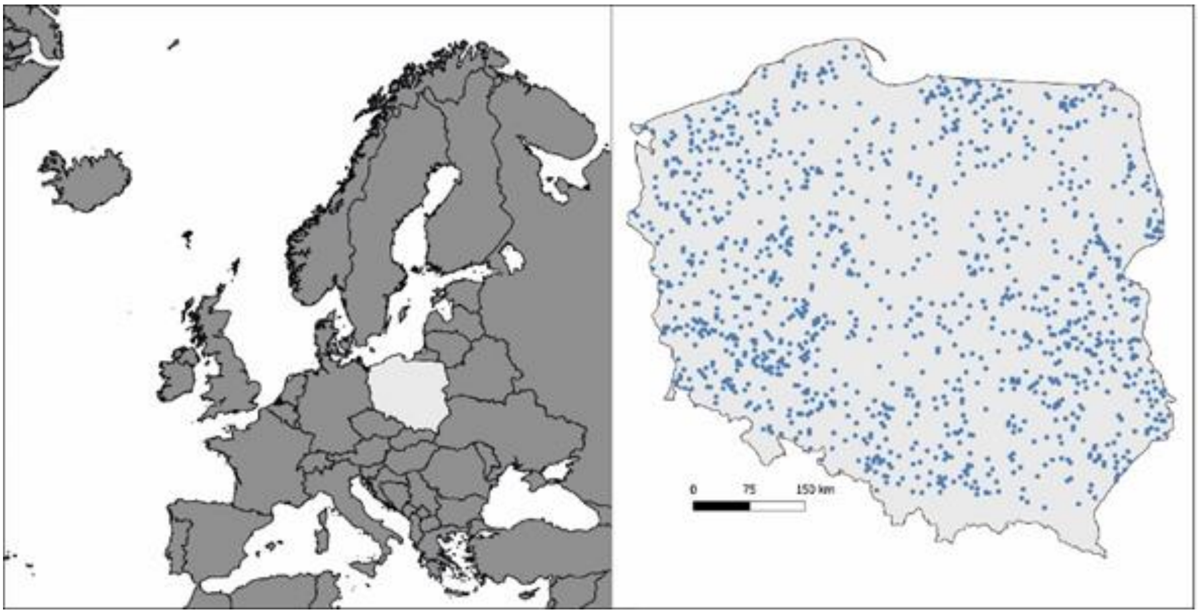

Fig. 1. Location of 2490 NFI oak-dominated sample plots (blue dots) in Poland (**Publication 1**)

Besides analyzing the influence of stand characteristics, we evaluated the impact of environmental factors on oak site productivity. The Digital Terrain Model (DTM) for Poland was used to characterize the topography of each plot. We determined that the slope of the sample plots ranges from 0 to 22.53 degrees; the average altitude above sea level of the sample plots is 176.22m.

We also used Poland's soil map and geological map at a scale of 1:500,000 to determine the type of soil and geology (Budzynska K et al., 2001; Jasiewicz & Stepinski, 2013). We classified into 10 soil types and 10 geological types (Table 1).

Table 1. Soil types and geological types estimated for the sample plots (**Publication 1**).

Type of soil	1, Cambisols; 2, Chernozems; 3, Fluvisols; 4, Gleysols; 5, Initials; 6, Luvisols; 7, Organics; 8, Podzols; 9, Rendzinas; 10, Umbrisols
Type of geology	1, Clays, silts and sands; 2, Eolian sands; 3, Gneisses; 4, Limestones; 5, Loams; 6, Loesses; 7, Sands and gravels; 8, Sands and silts; 9, Sandstones; 10, Others

Climate indicator values were obtained from the Global Climate Data - WorldClim (Hijmans et al., 2005). The resolution of monitored data was about 1 km x 1 km (Table 3)

In publication 2, the study materials were collected from 1464 sample plots (Fig. 2). The sample plots were established in oak stands with ages varying from 10 to 198 years and the number of trees per hectare ranged from 20 to 2275. The average diameter of oak is 32.46cm and the average height is 22.06cm.

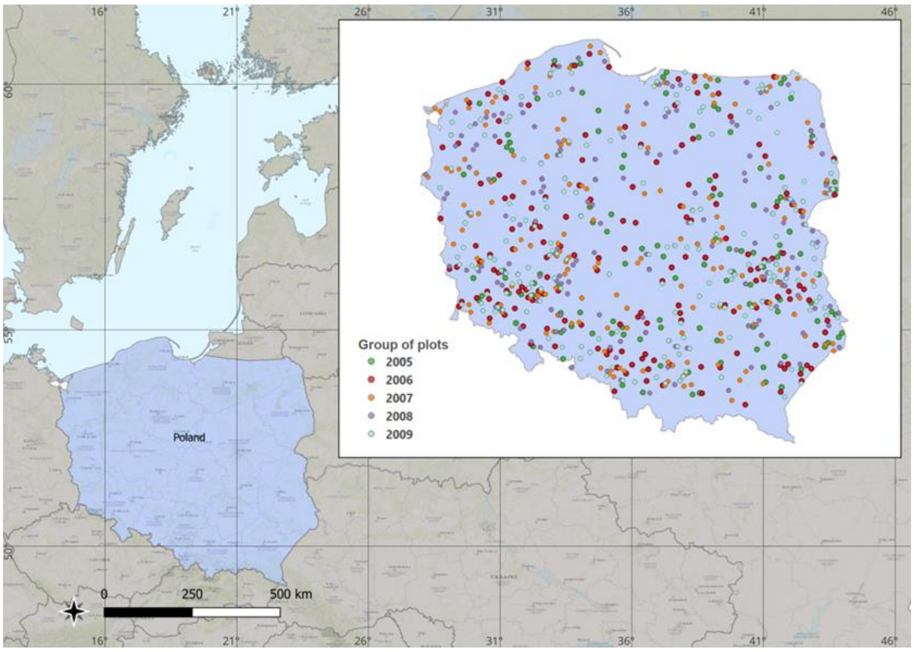

Fig. 2. Location of 1464 NFI oak-dominated sample plots in Poland. The colors represent groups of plots measured for the first time in a given year (**Publication 2**)

In publication 3, the study materials were collected from 1945 sample plots (Fig. 3). The sample plots were established in oak stands with ages varying from 9 to 205 years and the number of trees per hectare ranged from 20 to 2850. The average diameter of oak is 30.47cm and the average height is 20.93cm.

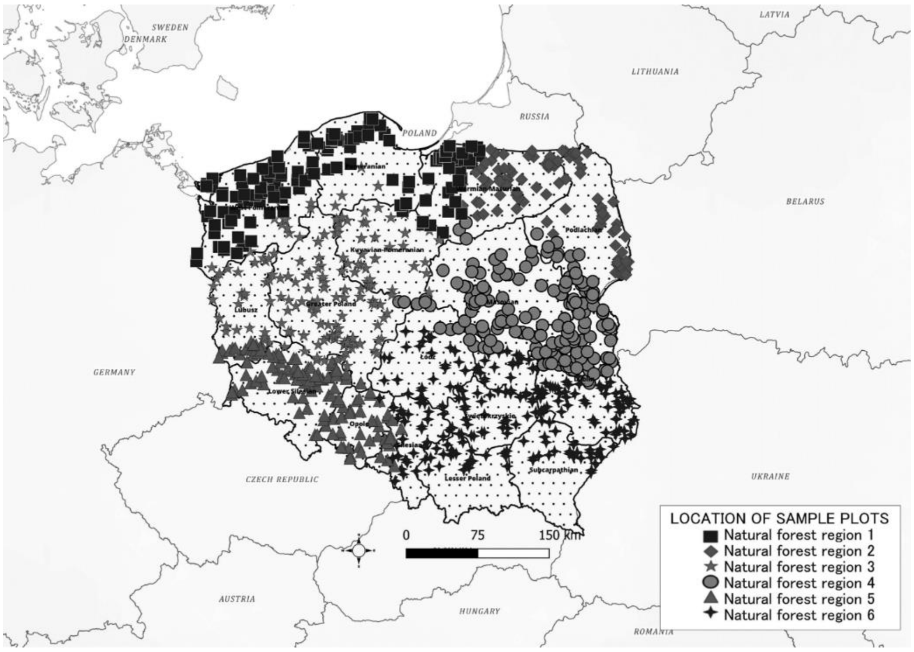

Fig. 3. Location of 1945 NFI oak-dominated sample plots in Poland. The symbols represent six natural forest regions distributing the sample plots (**Publication 3**)

We used the European Digital Elevation Model (EU-DEM) for Poland to describe the slope and altitude of sample plots. We determined that the slope of the sample plots ranges from 0 to 19.16 degrees; the average altitude above sea level of the sample plots is 167.46m.

We also used Poland's soil map and geological map at a scale of 1:500,000 to determine the type of soil and geology (Budzynska K et al., 2001; Jasiewicz & Stepinski, 2013). We classified into 18 soil types and 41 geological types.

Table 2. Soil types and geological types estimated for the sample plots (**Publication 3**)

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;

Type of geology	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;

Climate data were obtained from the Institute of Meteorology and Water Management stations in Poland for the period 2005-2020 (Table 3).

Table 3. Bioclimatic variables used to characterise the sample plots

Variable	Variable description
BIO1	Annual Mean Temperature (^{0}C)
BIO2	Mean Diurnal Range (Mean of monthly (max temp - min temp)) (^{0}C)
BIO3	Isothermality (BIO2/BIO7) (×100) (%)
BIO4	Temperature Seasonality (standard deviation×100) (%)
BIO5	Max Temperature of Warmest Month (^{0}C)
BIO6	Min Temperature of Coldest Month (^{0}C)
BIO7	Temperature Annual Range (BIO5-BIO6) (^{0}C)
BIO8	Mean Temperature of Wettest Quarter (^{0}C)
BIO9	Mean Temperature of Driest Quarter (^{0}C)
BIO10	Mean Temperature of Warmest Quarter (^{0}C)
BIO11	Mean Temperature of Coldest Quarter (^{0}C)
BIO12	Annual Precipitation (mm)
BIO13	Precipitation of Wettest Month (mm)
BIO14	Precipitation of Driest Month (mm)
BIO15	Precipitation Seasonality (Coefficient of Variation) (%)
BIO16	Precipitation of Wettest Quarter (mm)
BIO17	Precipitation of Driest Quarter (mm)
BIO18	Precipitation of Warmest Quarter (mm)
BIO19	Precipitation of Coldest Quarter (mm)

b. Model Development

In **publication 1**, we developed a model describing the relationship between SI and specific site variables characterizing growth conditions. SI was calculated for the sample plots using the top height growth model developed for oak in Poland (Socha, et al., 2020) based on the dynamic Korf equation (Anta et al., 2006) describing the change in the top height with age (formula 1).

$$SI = b_0 \left(\frac{H_0}{b_0}\right)^{\left(\frac{T}{T_0}\right)^{b_2}} \qquad (1)$$

Here, H_0 is the top height at age T_0; and T is the base age, equal to 100 years; b_0 and b_1 are the model parameters.

In **publication 2** and **publication 3,** we developed models to explain the dependence of the periodic annual volume increment on stand characteristics (**publication 2, publication 3**) as well as on environmental features such as topography, geology, soils, and climate (**publication 3**). The periodic annual volume increment is defined as the rate of volume growth of the tree or stand over some period of time (Ábri & Rédei, 2022b; Bayat et al., 2021) and calculated as the formula 2

$$PAIv = \frac{V_E + V_H - V_B}{T_j - T_i} \qquad (2)$$

where V_E is the volume at the end of the period; V_B is the 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 beginning 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 5 years.

The main steps for developing the productivity models in the thesis are described below. However, we also made necessary changes that were discussed explicitly in each publication.

Multicollinearity is often a severe problem when developing linear models. Collinearity can be the cause of unreliable models and a reduction in the predictive power of the model. We applied the variance inflation factor (VIF) for feature selection to solve this problem. The VIF value is 1 when there is no collinearity between the predictors. However, there is usually collinearity between predictors in practice. If predictors are highly collinear, higher VIF values are obtained. Many studies showed that a VIF value surpassing 5 or 10 indicates problematic collinearity (James et al., 2013; Melnychuk et al., 2017; Mendes et al., 2008). To calculate the VIF values, we used the "mgcv" package in the R program (R: Variance Inflation Factor). In **publication 2** and **publication 3**, we computed VIF values for all predictors and excluded the variable with the highest VIF. We repeated this process until all predictors had VIF values around 5.

The VIF can be computed for each variable using the formula 3:

$$VIF_{X_J} = \frac{1}{1 - R^2_{X_J|X_{-J}}} \qquad (3)$$

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

To assess the importance of the predictors included in the model, we also used the variable importance plots (VIP) function from the "VIP" package in the R program (Greenwell & Boehmke, 2020). This is a general framework for making variable importance plots from various types of machine learning models in the R program. In **publication 1** and **publication 3**, significant variables were selected from the set of variables related to stand characteristics, topographic features, bioclimatic, soil types, and geological types. Meanwhile, we only selected significant variables from the collection of variables related to stand characteristics in **publication 2** (Table 4).

Table 4. Factors included in modeling the site index and periodic annual volume increment

Response variable in the model	Factors included in the model				
	Stand characteristics	Bioclimatic	Topographic features	Soil types	Geological types
Site Index	Publication 1	Publication 1	Publication 1	Publication 1	Publication 1
Periodic annual volume increment	Publication 2 Publication 3	Publication 3	Publication 3	Publication 3	Publication 3

The selected variables were used to develop the GAM model. The general form of the GAM model is described by equation 4:

$$g(E(Y)) = \alpha + s_1(x_1) + \cdot\cdot\cdot + s_p(x_p) \qquad (4)$$

Where Y is the response variable; E(Y) denotes the expected value; g(Y) indicates the link function that links the expected value to the predictor variables $x_1, \ldots, x_p$; and $s_1(x_1), \ldots, s_p(x_p)$ denote smooth, nonparametric functions.

In developing the GAM model, we used coefficient tables, plots, and the ANOVA function of the "mgcv package" in the R program to analyze the deviation of the model to determine if any variable was a critical term to include. The ANOVA function was used to test whether a complex model with an extra variable captured the data significantly better than a model without that variable. If the p-value calculated was sufficiently low (we used the 0.05 level), we favor a more complex model with an additional variable. Otherwise, if the p-value was not less than 0.05, we chose the simpler model without an additional variable.

Model performance and potential overfitting in calculating adjusted R^2 were analyzed using 10-fold cross-validation. Using this method, the data was randomly divided into 10 parts, 9 used for training and 1 for the test. This process was repeated 10 times. Each time, a different tenth was reserved for the test. The method was implemented using the packages "gam" and "caret" in the R program (Ron Zacharski, 2018). In the last step, we evaluated the performance of the model using:

Mean absolute error:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad (5)$$

Root mean square error:

$$RMSE = \sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{n}} \qquad (6)$$

Adjusted coefficient of determination:

$$R^2_{adj} = 1 - (1 - R^2)\frac{n-1}{n-p-1} \qquad (7)$$

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

In **publication 3**, we also used the selected predictor variables to develop models for each specific natural forest region in Poland. Using the GAM model, the study tested the model's predictive ability when applied to smaller areas.

6. Main results

In **publication 1**, we developed a geocentric model for site productivity of oak in Poland using the NFI dataset representing a variety of site conditions and ages of oak stands. Site productivity expressed in SI was described by the stand characteristics and environmental variables. The study identified a significant relationship between SI and climatic factors. Specifically, temperature had the most noticeable effect on SI. Increasing the mean annual temperature slightly reduces the SI of oak stands. The SI of oak was also influenced by altitude. At altitudes below 200m, SI tended to increase with altitude. The study also demonstrated the variation in SI of oak stands according to soil type and geological type. In addition to environmental factors, we found that the SI of oak also depends on stand characteristics. The result confirmed that SI is related to stand density, as expressed by the stand density index. Increasing the stand density index up to about 1000 was associated with increasing SI, while further increases in the stand density index no longer affected SI. The age trend in SI, indicating a steady increase in site productivity for oak, may indicate that the role of this species in Poland's forest ecosystems will be even more significant in the future. The developed model explained approximately 55.1% (R^2_{adj}) of the variation in SI.

In **publication 2**, the study demonstrated the effect of age, height, basal area, and relative spacing index on the PAIv of oak stands in Poland. PAIv decreased significantly with the age of oak stands. Every 20 years, the PAIv of oak stands decreased by about 1.5 m^3/ha/year. This decrease was no longer evident for stands older than 100 years. Contrary to the influence of age, the study results showed a positive correlation between height and PAIv of oak stands. The most significant increase in PAIv was in the 25-38 m range. The effect of stand density on PAIv was also indicated by the relationship with the basal area and relative spacing index. These two variables were both in a proportional relationship with the PAIv of oak stands. However, the effect of basal area on PAIv was more marked than on the relative spacing index. The study reported that PAIv increases slowly when the basal area exceeds 30 m^2/ha or the relative spacing index exceeds 30%. The results also highlighted that the volume increment model developed with four predictor variables (age, height, basal area, and relative spacing index) had the highest explanatory power and the lowest error (R^2_{adj} = 64.6%; MAE = 1.80 m^3/ha/year; RMSE = 2.35 m^3/ha/year).

In **publication 3**, the study developed a GAM model explaining the influence of stand characteristics, climate, and topography on the PAIv of oak stands. The results indicated that age and basal area were responsible for the most significant amplitude of change in the PAIv. The PAIv decreased significantly with the age of oak stands. For oak stands older than 100 years, the rate of decrease has slowed. PAIv increased by approximately 3 m^3/ha/year for every 10m^2/ha increase in basal area. Top height also affected the volume increment of oak stands. However, above 30 m, this effect is no longer significant. The smallest effect of the relative spacing index was also found in the 20-35% range. In addition, the study noted the slight impact of temperature and precipitation in forming the volume increment of oak stands. The relationship between PAIv with the soil types and the topography types was analyzed in this study. PAIv tended to decline when the slope exceeded 5 degrees. In stands growing on black and gray land, the highest PAIv was observed. The developed GAM model had the best fitting statistics explaining 43.8 % (R^2_{adj})

of PAIv variability. Applying the GAM model to each specific natural forest region, The explanatory power of the model increases significantly and can reach 64.4% (R^2_{adj}).

7. Summary and conclusions

1. An extensive NFI dataset, representing a wide range of site conditions and a very large age range of oak stands, allowed the development of a geocentric model of site productivity for Poland. The developed geocentric model not only explained the effect of climate, soil and topographic variables, but also indicated the role of stand variables dependent on forest management.

2. The age trend of SI, indicating a steady increase in site productivity for oak, may indicate that the role of this species in Polish forest ecosystems will become even more important in the future.

3. The investigated dependencies of site productivity on age, climatic and stand factors are fundamental for the development of adaptation and mitigation strategies and for the promotion of sustainable forest management in the face of changing climatic conditions.

4. The PAIv of oaks in Poland is mainly determined by stand age, top height, basal area and RSI. The PAIv of oak gradually decreased with increasing age. The results of the study may be helpful in determining the intensity and frequency of silvicultural treatments in oak stands in order to achieve the optimal level of volume increment through appropriate regulation of basal area and density in relation to stand height and age.

5. Identified stand factors affecting volume increment will allow modelling of volume increment, which is important for predicting forest development and determining wood and biomass production and the potential for CO_2 sequestration by forest ecosystems.

6. In addition to the effect of stand characteristics, the PAIv of oak stands in Poland is influenced by climatic and topographic factors.

7. On a national scale, the volume increment of oak stands is influenced by temperature and precipitation. In addition, soil type and topography influence the PAIv of oak. However, 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.

8. The results of the study provide valuable information that can guide decision making in oak stand management. This knowledge can also help optimise the potential for timber production while increasing the forest's ability to sequester carbon, thereby contributing to climate change mitigation.

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8. Published scientific articles

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Drivers of site productivity for oak in Poland

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Abstract: The site index (SI) is the most commonly used and representative measure of the phytocentric approach; it evaluates the site productivity based on the stand height and age. In the case of mixed stands with complex structures, phytocentric methods are very limited, while in non-forest areas, they are not applicable. In situations where the applicability of phytocentric methods is limited, the site productivity is determined by geocentric methods. Geocentric methods allow direct modelling of site productivity, expressed by SI predicted from various environmental variables. The aim of this study was to develop a geocentric model for oak. Site productivity expressed by SI was described by the environmental variables and stand characteristics. To develop the SI model, we used the data from 2490 NFI plots with dominant oak species (*Quercus sessilis* and *Quercus robur*). A generalized additive model was used in modelling site productivity. We documented a significant relationship between SI and the environmental variables, age of stands and stand density. Furthermore, the site productivity for oak is shaped by climate factors, soil type, geology, and altitude. The model developed based on the geocentric method, explained 55.1% of the variation of SI.

Keywords: Site index, gam model, geocentric model, environmental effects.

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Introduction

Site productivity determines the potential to grow at a given site for a particular species. Information on site productivity is critical in forest management because it allows for the determination of forest functions and the proper quantification of ecosystem services provided by forests (Bengtsson et al., 2000; Duncker et al., 2012). Therefore, accurately determining site productivity is essential both for forest management and in the context of ongoing climate change, to predict its impact on site productivity and the role of a given species in future forest ecosystems. Knowledge of factors affecting site productivity allows us to select optimal silvicultural treatments and forest management practices aimed at introducing appropriate forest adaptation, and increase forest resilience to climate change (Sugawara & Nikaido, 2014; Seely et al., 2015; de la Fuente et al., 2018).

In forestry practices, the site index (SI) is the most widely used measure of site productivity, and it is estimated for a given species based on the stand height at a specific base age (Sugawara & Nikaido, 2014; Joan DeYoung, 2016). It is mostly determined by phytocentric methods (Hägglund B, 1981; Skovsgaard & Vanclay, 2008b). However, phytocentric methods are only appropriate for even-aged, undisturbed, and monoculture stands (Carmean & Lenthall, 1989; Huang & Titus, 1993; Skovsgaard & Vanclay, 2008b; Pokharel & Dech, 2011; West, 2015; Fu et al., 2018; Socha et al., 2020). In uneven-aged forests, the use of phytocentric methods is limited. Due to the complex vertical structure of uneven-aged stands, an early age height growth inhibition is observed (McQuilkin, 1975; Brüllhardt et al., 2020). Therefore, using stand height to determine SI may be inaccurate (McQuilkin, 1975; Barrett, 1978; Bettinger et al., 2017), making this method restricted to even-aged forests (Aertsen et al., 2011; Fu et al., 2018). Phytocentic methods may also be inappropriate in the case of young stands. Jaworski (2014) pointed out that in young stands, the dominant trees in the most favorable growth conditions represent the total potential site productivity. Ważyński (1967) found that the determination of the SI of pine stands up to 10 years old using height is inaccurate, because the height of young stands is not as strongly dependent on the environmental conditions as in later periods. Likewise, it is impossible to determine the site productivity by phytocentric methods for non-forest areas (Vanclay, 1994; Skovsgaard & Vanclay, 2008a; Weiskittel et al., 2011; Socha et al., 2020; Kędziora et al., 2020; Tymińska-Czabańska et al., 2021). Furthermore, a limitation of phytocentric methods is that they limit the possibility of identification of individual biological determinants of growth, precluding continuous mapping of SI across the landscape, or direct predictions based on environmental variables. To solve these problems, for direct site productivity modelling the geocentric method is used, in which SI is predicted from multiple environmental factors (Skovsgaard & Vanclay, 2008b; Weiskittel et al., 2011; West, 2014, 2015; Socha et al., 2020; Kędziora et al., 2020).

The physical factors affecting site productivity include climatic conditions, geology, soil conditions, geomorphology, and topography (Jaworski, 2003; Bošeľa et al., 2013; Bontemps & Bouriaud, 2014; Fiandino et al., 2020). The modifying effect of environmental on site productivity has been documented in numerous studies (Seynave et al., 2005; Monserud et al., 1990; Berrill & O'Hara, 2014). For example, the soil-site approach was used in modelling SI for Pacific Northwest Douglas fir (Monserud et al., 1990). The vegetation-based site type system used in the northern Rocky Mountains was related to site classes (Berrill & O'Hara, 2014). Seynave et al. (2005) developed a model that explains 64% of SI variance of Norway spruce and involves a wide spectrum of environmental variables. Fralish (1994) also demonstrated the influence of soil water holding capacity, slope position, and aspect on the SI of *Quercus alba* stands in the Illinois Shawnee Hills. In the study conducted on Okinawa Island, topographic variables were the main driver of site productivity (Miyamoto et al., 2018). Climate data sets available from meteorological observations and computational models may be crucial for the precision of SI modelling (Coops et al., 2000, 2010; Tymińska-Czabańska et al., 2021). Studies by Sharma and Parton (2018, 2019) demonstrated the influence of climate on the site productivity of red and white pine. Thus, geocentric methods may be also useful for modelling forest growth and site productivity under climate change (Dănescu et al., 2017; Brandl, 2020). A study conducted by Sharma et al. (2015) showed that the site productivity and height growth rate of jack pine and black spruce will be reduced by the warming climate. de Wergiforsse et al. (2022) demonstrated that the productivity of oak and beech forests is negatively affected by increasing air temperatures and decreasing annual precipitation.

In the last decades, ongoing changes in site conditions in Central Europe may have begun to favor oak over conifers (Hanewinkel et al., 2012; Dyderski et al., 2018). So far, despite its significant ecological and economic role in forestry, the productivity of oak has received less attention. The research conducted so far has a rather local character, and has been concerned mostly with small scale forestry (Graney, 1977; Dobrowolska, 2008; Nunes et al., 2015; Bijak & Sacewicz, 2018; Tymińska-Czabańska et al., 2021). Thus, the development of country scale geocentric SI models for oak could partly close this knowledge gap and contribute to our understanding of the impact of multiple environmental factors on site productivity for this important forest-forming tree species. Reliable determination of site productivity is critical for effective forest management in changing climate conditions (Bontemps & Bouriaud, 2014; Sharma et al., 2015; Sharma & Parton, 2018, 2019; de Wergifosse et al., 2022). Therefore, the study of factors affecting site productivity for oak stands is of great importance, both from practical and scientific points of view.

This study aimed to determine the relationship between site productivity for oak and environmental variables, such as climate, topography, geology, and soil type. Actual site productivity may also be modified by forest management; therefore, in the modelling, we additionally acknowledged the stand characteristics as SI predictors. To provide a country-scale picture of site productivity, we used a large data set from the National Forest Inventory (NFI) that allowed for a full representation of the wide variation of site conditions and stand characteristics.

Materials and methods

Sample Plot Data

This study used NFI data from Poland. On the basis of the measurements of the trees in sample plots, basic properties were determined and calculated for each plot:
– Quadratic mean diameter at breast height (DBH);
– Top height (TH), calculated as the mean height of the 100 trees of largest DBH per hectare;
– Stand density index: Calculated by the average DBH (*Dg*) and the number of trees per ha (*N*) using the Reineke (1933) formula (1):

$$SDI = N \times \left(\frac{Dg}{25}\right)^{1.605} \quad (1)$$

The study materials were collected from 2490 sample plots with dominant oak species (*Quercus sessilis* and *Quercus robur*). The sample plots were set up with an area of 200 or 500 m², and the number of trees per hectare ranged from 20 to 2850 trees (Table 1). The sample plots represented a wide range of ages, varying from 9 to 210 years.

Topographic and climate data

To characterize the topography of individual plots, the Digital Terrain Model (DTM) for Poland was used. On the basis of DTM, we determined the slope as the angle of inclination of the terrain, expressed in degrees (ArcGIS, 2021).

The aspect was calculated as the downslope direction of the maximum rate of change in value from each cell to its neighbours. The aspect can be thought of as the slope direction (ArcGIS, 2021).

The topographic wetness index (TWI, equation 2) characterizes the moisture conditions in a given location related to the terrain. It is commonly used

Table 1. Basic characteristics of the sample plots

Characteristic	Mean	Minimum	Maximum	Standard Deviation
Plot area (m²)	339.28	200	500	95.71
Age (Years)	74.69	9	210	37.14
Height (m)	21.36	3.50	31.30	7.18
Diameter (Cm)	31.49	7.00	135.30	15.83
Basal area (m²/ha)	16.50	0.19	78.06	9.77
Density (trees/ha)	636.81	20	2850	359.44
SDI (trees/ha)	748.23	6.48	3246.84	501.06
Slope (degrees)	2.59	0.06	22.53	2.52
Altitude (m)	176.22	3.27	537.86	82.93
Aspect (degrees)	179.51	0.84	359.72	107.37
Topographic wetness index	8.42	5.53	15.83	1.41

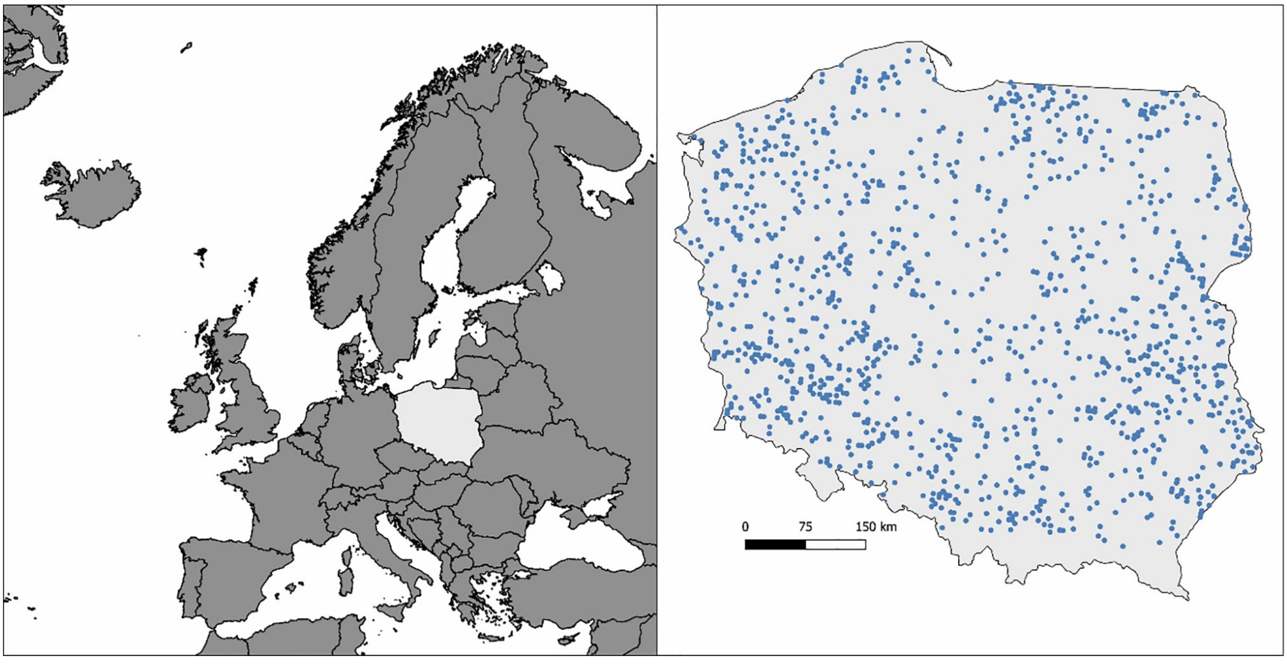

Fig. 1. Location of 2490 NFI oak dominated sample plots (blue dots) in Poland

to quantify topographic control of hydrological processes (Sørensen et al., 2006).

$$TWI = ln\left(\frac{SCA}{\tan\varphi}\right) \tag{2}$$

Here, *SCA* is the Specific Catchment Area and is defined as the contributing area per unit width of contour (in pixels); φ is the slope angle, assuming the properties of the soil are uniform. To calculate these value, a DTM for Poland was used. The topographic wetness index is unitless.

We used the soil map of Poland at the scale 1:500,000 (Budzynska K et al., 2001) and the geological map of Poland at a scale of 1:500,000 (Jasiewicz & Stepinski, 2013) to determine the type of soil and type of geology.

The values of climate indicators were obtained from the WorldClim - Global Climate Data (Hijmans et al., 2005). The climate parameters (Table 3) were developed for 1950–2000. The resolution of the monitored data was approximately 1 km × 1 km.

Model Development

SI was determined for the sample plots using the TH growth model developed for oak in Poland (Socha et al., 2020) based on the dynamic Korf equation (Anta et al., 2006) describing change in the TH with age (equation 3).

$$SI = b_0\left(\frac{H_0}{b_0}\right)^{\left(\frac{T}{T_0}\right)^{b_2}} \tag{3}$$

Here, b_0 and b_1 are the model parameters; H_0 is the top height at age T_0; and T is the base age, equal to 100 years. This model has been used in several studies related to the site index, and has proven accurate when applied to oak stands (Sharma et al., 2011; Ercanli et al., 2014; Socha et al., 2020; Tymińska-Czabańska et al., 2021).

Among the many possible modelling methods, Aertsen et al (2010) demonstrated the usefulness of the Generalized Additive Model (GAM), which provides good predictability and allows the analysis of a wide range of data types. The GAM model enables making estimates for multivariate variables using the additive approximation of the regression function by substituting the linear function of the explanatory variable with non-parametric functions. These can be estimated using, for example, smoothing spline functions (splines) (Hastie & Tibshirani, 2017; Wood, 2017). GAM strikes a balance between an interpretable but unbiased linear model and highly flexible "black box" learning algorithms (Hastie & Tibshirani, 2017; Wood, 2017). GAM allows us to control the smoothness of prediction functions to prevent overfitting. We can directly solve the bias/variance trade-offs by controlling the swings of the prediction functions (Hastie & Tibshirani, 2017; Wood, 2017).

Table 2. Soil types and geological types estimated for the sample plots

Type of soil	1. Cambisols; 2. Chernozems; 3. Fluvisols; 4. Gleysols; 5. Initials; 6. Luvisols; 7. Organics; 8. Podzols; 9. Rendzinas; 10. Umbrisols
Type of geology	1. Clays. silts and sands; 2. Eolian sands; 3. Gneisses; 4. Limestones; 5. Loams; 6. Loesses; 7. Sands and gravels; 8. Sands and silts; 9. Sandstones; 10. Others

Table 3. Characteristics of the climate variables estimated for sample plots

Variable	Variable description	Mean	Minimum	Maximum	Standard Deviation
BIO1	Annual Mean Temperature (°C)	7.65	5.80	9.10	0.60
BIO2	Mean Diurnal Range (Mean of monthly (max temp − min temp)) (°C)	8.19	6.20	9.40	0.56
BIO3	Isothermality (BIO2/BIO7) (×1°°) (%)	26.72	23.00	31.00	1.79
BIO4	Temperature Seasonality (standard deviation×1°°) (%)	7791.63	6654.00	8891.00	424.22
BIO5	Max Temperature of Warmest Month (°C)	23.21	20.40	24.90	0.72
BIO6	Min Temperature of Coldest Month (°C)	−6.89	−9.80	−3.80	1.21
BIO7	Temperature Annual Range (BIO5-BIO6) (°C)	30.11	24.90	33.00	1.42
BIO8	Mean Temperature of Wettest Quarter (°C)	17.15	14.90	18.60	0.59
BIO9	Mean Temperature of Driest Quarter (°C)	−1.05	−4.10	3.50	1.66
BIO10	Mean Temperature of Warmest Quarter (°C)	17.18	14.90	18.60	0.54
BIO11	Mean Temperature of Coldest Quarter (°C)	−2.90	−5.30	−0.60	1.06
BIO12	Annual Precipitation (mm)	592.39	489.00	957.00	61.08
BIO13	Precipitation of Wettest Month (mm)	80.62	63.00	140.00	8.23
BIO14	Precipitation of Driest Month (mm)	27.59	20.00	46.00	3.34
BIO15	Precipitation Seasonality (Coefficient of Variation) (%)	35.39	21.00	48.00	5.21
BIO16	Precipitation of Wettest Quarter (mm)	225.45	174.00	384.00	25.30
BIO17	Precipitation of Driest Quarter (mm)	89.75	67.00	145.00	11.05
BIO18	Precipitation of Warmest Quarter (mm)	225.13	174.00	384.00	25.37
BIO19	Precipitation of Coldest Quarter (mm)	100.05	76.00	154.00	15.83

We developed models describing the relationship between SI and the specific site variables characterizing the growth conditions of oak stands. To determine the importance of the variables, we used the vip (variable importance plots) function of the vip package in R ("Package 'vip,'" 2020). With vip, it is possible to obtain a consistent interface to calculate variables important for many types of supervised learning models across several packages, as well as an experimental function for quantifying the strength of potential interaction effects (Štrumbelj & Kononenko, 2014). The most important variables were used to develop the SI model.

The structure of GAM is:

$$g(E(Y)) = \alpha + s_1(x_1) + \cdots + s_p(x_p),$$

where Y is the dependent variable (i.e., what we are trying to predict); E(Y) denotes the expected value; g(Y) denotes the link function that links the expected value to the predictor variables $x_1, \ldots, x_p$; and $s_1(x_1), \ldots, s_p(x_p)$ denote smooth, nonparametric functions.

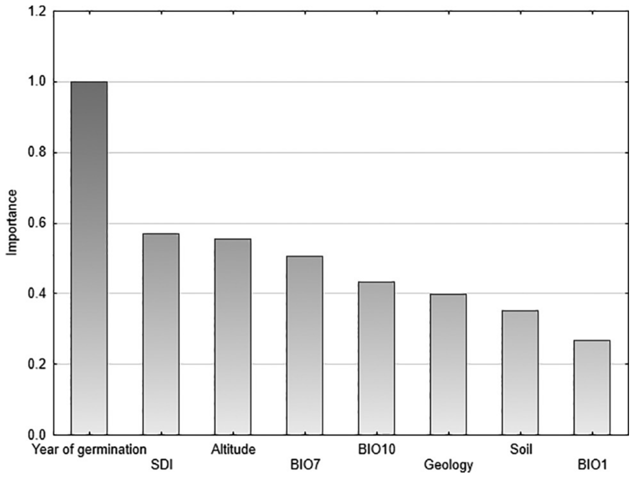

Fig. 2. Important variables for developing the GAM model

The model performance, and possible overfitting in calculating adjusted R^2, were analyzed by the use of 10-fold cross-validation. The procedure was performed using the R language package gam and package caret ("R Core Team," 2020). In the last step, we evaluated the performance of the model using:

– Mean Absolute Error: $MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$

– Root Mean Squared Error: $RMSE = \sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{n}}$

– Adjusted Coefficient of Determination:

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

where y_i terms are the observed values, y_i terms are the model values, n is the number of errors, p denotes the number of parameters used in the model, and R^2 is the coefficient of determination.

Results

The results of the importance of variables analysis indicated that eight variables have the most significant influence on SI (Fig. 2).

Selected explanatory variables were used in the development of the site productivity model. The results of modeling using the GAM show effect of particular variables on SI (Figs 3–8). Firstly, we identified the influence of bioclimatic characteristics on SI. Site productivity of oak stands significantly decreases (by almost 6 m) with increasing annual mean temperature (Fig. 3a). SI also decreases with an increasing annual temperature range. With an increase of the annual temperature range from 28 to 33 °C, SI decreases by about 3.5 m (Fig. 3b). Therefore, in areas with lower annual temperature fluctuations, the site productivity for oak is higher (Fig. 3b).

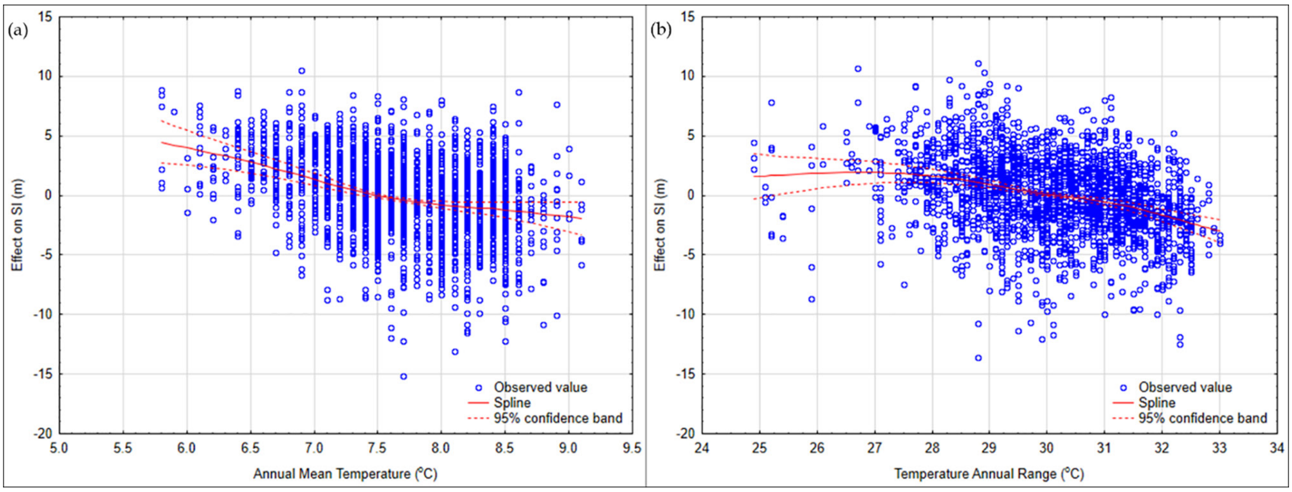

Fig. 3. Partial effects of the annual mean temperature (a) temperature annual range (b) on the site index for oak

In contrast to the mean annual temperature, an increase in the mean temperature of the warmest quarter results in an increase in site productivity for oak. The SI increases more than 11 m when the mean temperature of the warmest quarter increases by about 4 °C (Fig. 4).

The SI for oak is slightly influenced by the altitude. An increase in altitude from 0 m to 200 m above sea level led to a slight increase in SI. However, a further increase of altitude had almost no effect on SI (Fig. 5).

We also found a significant influence of soil type on SI. The highest SI was observed in stands growing on fluvisols and luvisols soil types (Fig. 6). The site productivity was also slightly affected by geology type. The analysis results showed that the highest SI values of oaks were focused on the gneisses geological type (Fig. 7).

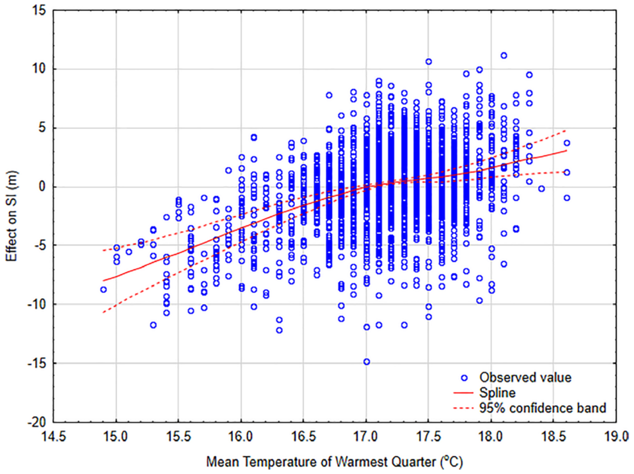

Fig. 4. Partial effects of mean temperature of the warmest quarter on the site index for oak

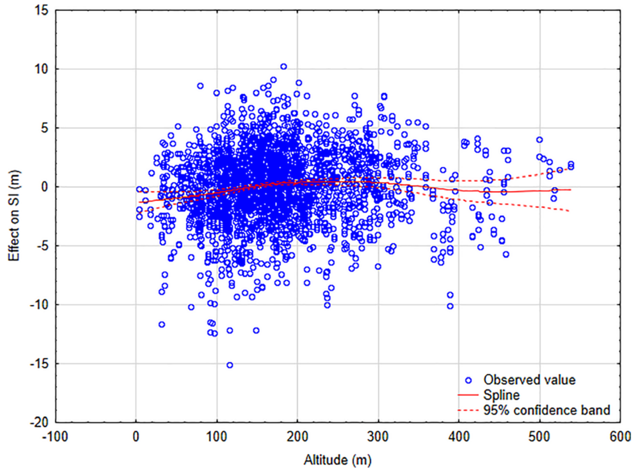

Fig. 5. Partial effects of altitude on the site index for oak

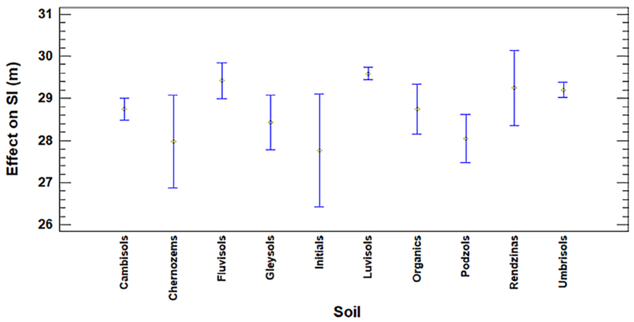

Fig. 6. Partial effects of soil type on the site index for oak

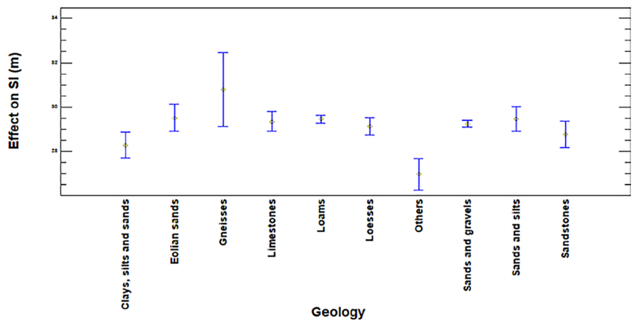

Fig. 7. Partial effects of geology type on the site index for oak

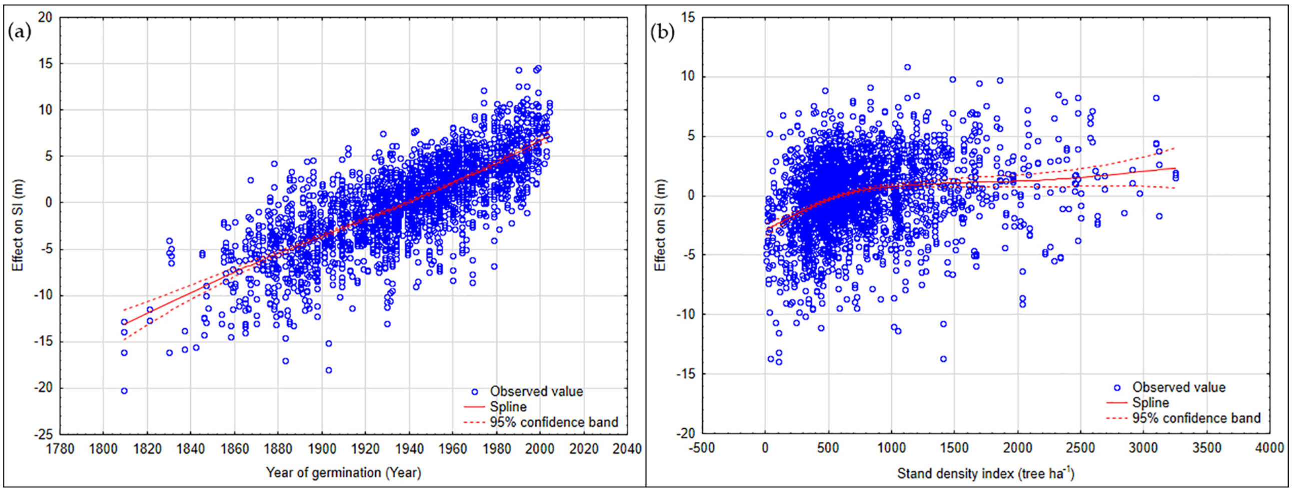

Fig. 8. Partial effects of year of germination (a) and stand density index (b) on the site index for oak

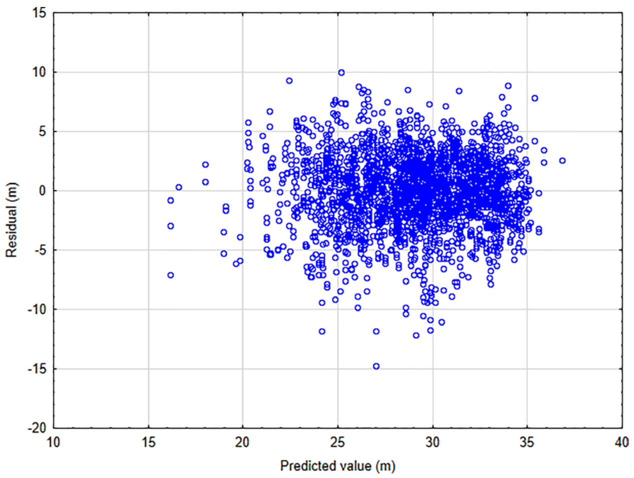

Fig. 9. Residual SI versus values predicted by the developed GAM model for oak

In addition to the influence of environmental variables, we documented a strong effect of age of germination on SI (Fig. 8a). Oak stands showed a strong age trend in site productivity manifested by an increase in SI with year of germination. Stands established in subsequent years showed higher SI values. The observed age trend indicates that the change in the SI was about 11 m per 100 years. In addition to site variables, we also documented the influence of SDI on the SI for oak. A significant increase of SI was observed with an increase of SDI, to the value of about 1000. A further increase of SDI did not significantly change the SI (Fig. 8b).

The full model, describing SI based on environmental variables, age of germination, and SDI, explained about 55.1% of SI variability. The mean absolute error of the model (MAE) was 2.40 m and the root mean square error (RMSE) was 3.14 m. R^2_{adj} calculated on the basis of 10-fold cross-validation was 49%, suggesting model overfitting was not a concern. This indicated the good predictive ability of the developed model. The diagnostic plot (Fig. 9) of the residual values shows no correlation with the values of SI predicted by the GAM model.

Discussion

We identified the most important factors determining site productivity for oak. In our analyses, we included both variables inherent to the site and variables dependent on forest management, such as

Table 4. Estimated parametric coefficients of GAM model

Variable	Estimate	Standard error	t value	Pr(>|t|)
Intercept	28.0123	1.9119	14.652	<0.0001
Geology Eolian sands	0.7459	0.5905	1.263	0.20665
Geology Gneisses	3.3210	1.2405	2.677	0.00748
Geology Limestones	1.0816	0.5113	2.115	0.03451
Geology Loams	0.6390	0.4286	1.491	0.13612
Geology Loesses	0.5215	0.5006	1.042	0.29755
Geology Others	0.1371	0.6764	0.203	0.83939
Geology Sands and gravels	0.6105	0.4235	1.442	0.14951
Geology Sands and silts	0.9376	0.5650	1.659	0.09716
Geology Sandstones	0.9939	0.6064	1.639	0.10134
Soil Cambisols	0.4330	1.8782	0.231	0.81770
Soil Chernozems	−0.4269	2.0186	−0.211	0.83254
Soil Fluvisols	0.7180	1.9051	0.377	0.70628
Soil Gleysols	0.2628	1.9271	0.136	0.89152
Soil Initials	1.9000	2.1672	0.877	0.38073
Soil Luvisols	0.7482	1.8696	0.400	0.68903
Soil Organics	0.3869	1.9212	0.201	0.84042
Soil Podzols	−0.5842	1.9172	−0.305	0.76061
Soil Rendzinas	0.1061	1.9782	0.054	0.95723
Soil Umbrisols	0.5429	1.8724	0.290	0.77187

Table 5. Approximate significance of smooth terms for variables used in GAM model

Variable	Effective degrees of freedom	Reference degrees of freedom	F	p-value
Year of germination	6.236	7.359	263.244	<0.0001
Altitude	7.361	8.346	6.120	<0.0001
BIO1	4.247	5.305	6.194	<0.0001
BIO7	6.845	7.855	7.467	<0.0001
BIO10	6.123	7.190	5.748	<0.0001
SDI	5.632	6.812	23.317	<0.0001

stand characteristics. The study documented a strong relationship between SI and climatic factors. Moreover, we showed that site productivity of oak is influenced by SDI, altitude, soil, and geology. However, our study indicated that site productivity for oak is subject to changes caused by non-static site factors, as evidenced by the age trend in the site index. The developed model explained about 55.1% of the variance of SI.

We found that the climatic conditions affect the site productivity for oak. An increase in mean annual temperature slightly decreases the site productivity for oak. However, oaks are known as more thermophilic and relatively resistant to drought or strong winds, so a higher mean annual temperature, which is associated with high evapotranspiration, may not be optimal for the growth and productivity of oak stands (Browne et al., 2019). Therefore, climate change associated with increasing temperatures may not positively affect site productivity for oak in some areas. A study on three European oak species also showed that their root length growth and height growth decreased with increasing air temperature (Arend et al., 2011). We detected a significant impact of annual temperature range on site productivity, which is biologically plausible and consistent with the ecological requirements of the oak (Johnson et al., 2002). An increase in the annual temperature range, which is indicated in climate continentality, significantly decreased the SI for oak. Cold winters and the continental climate are not particularly favorable for sessile oaks, and are a limiting factor for their occurrence (Mérian et al., 2011). However, surprisingly, increasing mean temperature of the warmest quarter increases the SI for oak. This may suggest that climate change-related increases in temperatures during the warmest period will not be a limiting factor for oak growth.

Our results indicated a slight increase of SI with increasing altitude up to 250 m. These results are consistent with studies for oak from Southeastern Poland (Tymińska-Czabańska et al., 2021), in which an increase in elevation to about 250 m was also accompanied by an increase in the SI for oak. These results are also consistent with the work of Bresson et al. (2011) on the effect of altitude on the growth of oak stands (Bresson et al., 2011). The relationship between the SI of northern red oak and elevation was also documented in a study conducted in the Appalachian Mountains of North Carolina (Mcnab, 2010). The relationship of SI to elevation is most likely related to soil moisture; wetter sites at low elevations may limit growth somewhat. Oak stands growing at the lowest elevations may also be vulnerable to early frost. Conversely, growth inhibition above 250 m may be explained by less favorable thermal conditions.

We also documented the relationship between site productivity and soil types. Oak stands grown on fluvisols and luvisols soil types, characterized by their stratified structure, relatively high humus content, and clay particles, showed the highest productivity. In addition to soil type, we found that the SI of oak stands was also influenced by the type of geological substratum. The highest value of SI was marked in the gneisses, with a broad spectrum of metamorphic rocks. A relationship between soil type and SI was also reported by Bijak & Sacewicz (2018). A study on the impact of environmental factors on site productivity in southern Poland (Tymińska-Czabańska et al., 2021) and the influence of soil characteristics on oak secondary forests in China (Sun et al., 2021) also demonstrated the relationship between soil and geology with site productivity.

In the context of climate change and anthropopressure, which have been crucial to the functioning of forest ecosystems in recent decades, a quantitative assessment of trends in site productivity is very important. Base on a large database covering a wide spectrum of site conditions and a large age range of stands, we were able to describe long-term changes in the site productivity for oak in Poland. We found that site productivity is sharply determined by the year of germination. The documented age trend in site productivity is likely due to the effect of climate and environmental change, and has been observed for different species and biomes (di Filippo et al., 2010; Nunes et al., 2015; de Wergifosse et al., 2022). The influence of non-static factors, such as increasing nitrogen deposition and rising temperatures and CO_2 concentrations, has been recognized as the main cause of site productivity increases (Nunes et al., 2015; de Wergifosse et al., 2022). Site index is a good indicator of the effect of climate change on tree growth and site productivity (Socha et al., 2016; Pau et al., 2022). The ability to capture changes in productivity using differences in SI values is due to the different responses of trees of different ages to changes in growth conditions. The growth of young trees fully reflects the current potential of the site, while the oldest trees react minimally with increased height growth to improved site conditions. Hence the paradox that under identical site conditions, young trees have a much higher SI than trees of older age classes.

Our findings are in line with the results of other studies (Kozak & Holubets, 2001; Tymińska-Czabańska et al., 2021). The demonstrated changes in site productivity have important implications for forest management. Increased site productivity causes trees to reach certain dimensions in a shorter timeframe, which leads to increased stand density (Ouyang et al., 2019). If trees grow faster as a result of increasing site productivity, they will reach harvestable size sooner, which decrease the rotation age or leads to a shortening of the natural life span (Körner, 2017). Our results show that SI is related to stand density, as expressed by the SDI. An increase in SDI up to around 1000 is accompanied by an increase in SI, while a further increase in SDI no longer affects SI. This relationship has a twofold significance. First, it indicates a stimulating effect of stand density on oak height growth. On the other hand, however, the dependence of SI on SDI may result in an underestimation of site productivity as measured by SI in stands with lower densities, characterized by an SDI value of up to approximately 1000, which should be taken into account when calculating the site productivity for oak. The stimulating effect of stand density on the height growth of forests has been also previously reported. A study on loblolly pine showed a positive correlation between stand density and height (Sharma et al., 2002). Long-term thinning experiments on mineral soil sites in southern and central Finland showed an increase in the dominant height of Scots pine with increasing stand density (Mäkinen & Isomäki, 2004). Recent studies conducted in Poland also indicated a stimulating effect of increased stand density on Scots pine height growth (Socha et al., 2021). Another study in southern Finland showed that the height of clonal hybrid aspens grows linearly with age, and grows higher at higher planting densities (Lee et al., 2021). Several studies have also been performed to determine the desirable SDI of each species (Reineke, 1933; Woodall et al., 2005). In light of our results, research on SDI should also take into account its impact on height growth dynamics.

The observed trends in SI and the relationship of SI and stand density indicate some limitations of the SI concept that should be taken into account when assessing site productivity for oak based on age and stand height. The results emphasized the effect of climate conditions on site productivity for oak. In the context of climate change, knowledge of climate factors and their impact on site productivity for oak is extremely important. The relationships established allow the future role of this species in forest management to be assessed. Further analysis is required to identify the optimal outcome, from the point of view site productivity, of site-specific silvicultural treatments that, inter alia, may determine SDI and stand volume increment.

Conclusions

An extensive NFI data set, representing a wide spectrum of site conditions and a very large age range of oak stands, allowed the development of a geocentric model of site productivity for Poland. The developed geocentric model explained the effect of site climate, soil, and topographic variables, but also indicated on the role of stand variables dependent on forest management. The use of GAM allowed for analysis of the effect of individual variables on SI, with all other variables fixed. The age trend in SI, indicating a steady increase in site productivity for oak, may indicate that the role of this species in Poland's forest ecosystems will be even more significant in the future. The investigated dependences of site productivity on age, as well as climatic and stand factors, are fundamental in the light of changing climatic conditions for creating adaptation and mitigation strategies and promoting sustainable forest management.

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Modeling the Effect of Stand Characteristics on Oak Volume Increment in Poland Using Generalized Additive Models

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Abstract: Volume increment is one of the main concerns in forestry practice. The aim of our study was to examine the impact of factors influencing the periodic annual increment of oak. To meet our objective, we used measurement data from the national forest inventory in Poland from 2005 to 2019 for oak-dominated stands. Our study used data of 1464 sample plots with dominant oak species (*Quercus sessilis* Ehrh. ex Schur and *Quercus robur* L.) measured within the national forest inventory in Poland. We developed models explaining the dependence of the periodic annual volume increment on stand characteristics using the generalized additive model. The generalized additive model allows us to analyze each variable's effect on the dependent variable, with all other variables fixed. We documented the effect of age, height, basal area, and relative spacing index (RSI) on the periodic annual volume increment (PAIv) of oaks in Poland. The PAIv of oaks decreased gradually as the tree aged. The dependence of the PAIv on stand density was shown through its relationship with the basal area and RSI. The developed model explained about 64.6% of the periodic annual volume increment variance.

Keywords: periodic annual volume increment; GAM; stand density; basal area; RSI

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1. Introduction

The volume increment of stands is one of the most important indicators of forest dynamics. Knowledge of volume increment allows for forecasting and developing appropriate forest management plans [1,2]. It is also vital in the context of determining biomass production and the potential for CO_2 sequestration by forest ecosystems [3–6]. Identifying how individual stand factors influence volume increment can be useful in forestry practice and is of growing importance in sustainable forest management.

Essentially, increment describes the rate at which the tree or stand increases in weight or size over a given period of time [7]. The measurements on sample plots in national forest inventories (NFIs) can provide accurate and comprehensive information on the various components of the annual increment [8]. Instead of annual measurements, periodic surveys at n-year intervals are carried out; then, the recorded increment in height, diameter, and volume must be divided by n and is called the periodic annual increment [9]. The periodic annual increment is a more realistic indicator of a tree's capacity (or a stand's) to grow to a given age or size. The volume increment can be influenced by environmental factors and tree characteristics [7,10]. Toledo et al. [11] demonstrated that competition from neighboring trees is an essential biological factor limiting volume growth. Some studies have shown that stand volume increases with narrower plantation spacing. However, when a certain threshold is reached, the narrow plantation spacing can decrease the volume growth rate [12]. A study on Oriental beech (*Fagus orientalis* Lipsky) in Iran showed that stand volume at the beginning of the measurement period and tree diameter had the greatest impact on the variation in volume increment [13]. The influence of these on forest growth, productivity, and biodiversity can be important for sustainable forest management [14,15].

Periodic change in volume is the foundation of many forest growth and productivity models [8,10,13,16–18] and is necessary for determining sustainable harvests in unevenly aged forest management [2,19].

Regression analyses are often used in forest growth models to predict the response of a dependent variable to changes in the relationship with the independent variables [20]. However, due to the complex relationship between the dependent and independent variables, as well as the interaction between the independent variables in the environment, regression analysis may be limited [2,21]. Regression models often lose their ruggedness due to strong linear correlations between independent variables. In addition, regression models do not automatically take care of nonlinearities and do not work with categorical variables [22]. Among the many possible modeling methods, Aertsen et al. demonstrated the usefulness of generalized additive models (GAMs) for the prediction of a site index in Mediterranean mountain forests [23]. GAMs enable making estimates for multivariate variables using the additive approximation of the regression function by substituting the linear function of the explanatory variable with nonparametric functions. The use of a GAM allows us to analyze the effect of each individual variable on the dependent variable, with all other variables fixed. GAMs can model highly complex nonlinear relationships when the number of potential predictors is large, and it also works with categorical variables [24,25].

The *Quercus* genus belongs to the Fagaceae family; in Europe, 27 native species of *Quercus* genus have been found [26,27]. This study focused on *Quercus robur* L., known as pedunculate or English oak, and *Quercus petraea* (Matt.) Liebl., known as sessile oak. These two species occur in many sites as a major component of temperate deciduous mixed forests. The large ecological amplitude is responsible for the wide range of this species at different sites [28]. Oak is of great economic importance, and predicted changes in site conditions may increase their importance in forest ecosystems in Europe in the future [29,30].

Therefore, the aim of our study was to examine the impact of factors influencing the periodic annual increment of oak. To meet our objective, we used measurement data from the national forest inventory activities in Poland from 2005 to 2019 for oak-dominated stands. This extensive data set allowed us to analyze the relationship between the periodic annual increment and the features of oak stands. The results can extend our knowledge of how individual stand factors affect the periodic annual increment patterns for oak, which can be of significant operational and theoretical importance.

2. Materials and Methods

2.1. Sample Plot Data

The material used in this study was measurement data from the NFI activities in Poland from 2005 to 2019. The measurement period started in 2005, with a length of one inventory cycle being 5 years. The NFI measurements started in 2005. Every year, a fifth of the sample plots determined for the whole country were measured. Thus, for plots measured for the first time in 2005, the data covered three periods: The first covered 2005–2009, the next covered 2010–2014, and the third period was 2014–2019. For plots measured for the first time in subsequent years, the increment covered two incremental periods. The study used data collected from 1464 sample plots of three cycles with the dominant oak species (*Quercus sessilis* and *Quercus robur*) (Figure 1). The analyses did not distinguish between the two oak species as they are very similar in terms of growth and productivity [31]; moreover, hybrids that are difficult to assign unambiguously to either species are very common in Poland.

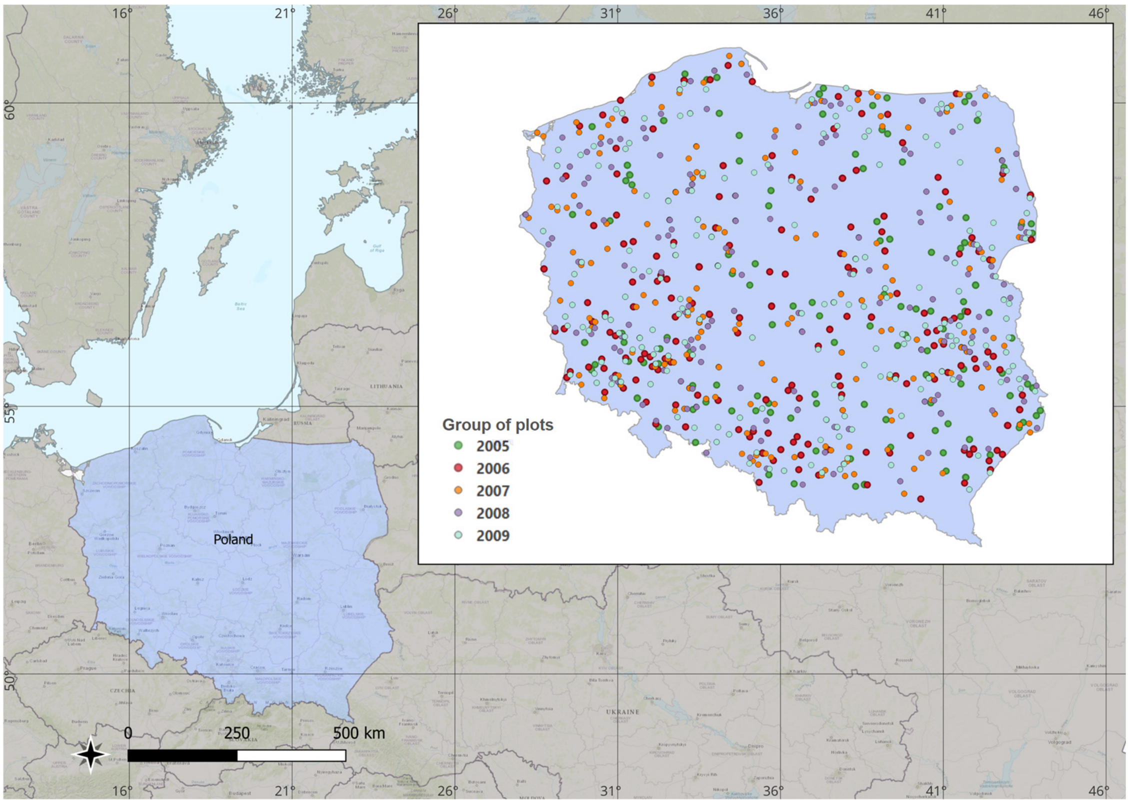

Figure 1. Location of 1464 NFI oak-dominated sample plots in Poland. The colors represent groups of plots measured for the first time in a given year.

The sample plots were set up with an area of 200 or 500 m^2. The basic properties were determined and calculated for each plot:

– Density (number of trees per hectare);
– Quadratic mean diameter at breast height (DBH), in centimeters;
– Top height (TH), calculated as the mean height of the 100 trees with the largest DBH per hectare, in meters;
– Total basal area (total cross-sectional area of trees at breast height):

$$G = \frac{\pi \times DBH^2}{40000} \quad (1)$$

– Stand volume (V):

$$V = g \times h \times f \quad (2)$$

where g is the basal area; h is the height of the tree; f is the form factor, which refers to the characteristic shape of the tree and is the reduction factor of the cylinder volume to the actual tree volume. For our study, we considered the form factor functions of Bruchwald et al. [32]:

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

– The stand density index(SDI) was calculated by the average DBH and the number of trees per ha (N) using the Formula (4) [33]:

$$SDI = N \times \left(\frac{DBH}{25}\right)^{1.605} \quad (4)$$

– The relative spacing index (RSI) was calculated as the ratio, which was expressed as a percentage, between the average distance among trees and the top height of the stand, according to Formula (5) [34,35]:

$$RSI = \frac{AS}{TH} * 100 = \frac{10^4 \times \sqrt{\frac{2}{N \times \sqrt{3}}}}{TH} \quad (5)$$

where TH is the top height of the stand, N is the number of trees per hectare, and AS is the average spacing between trees. For the estimation of AS using N, trees were assumed to be positioned on a triangular grid.

– The periodic annual volume increment (PAIv) is the volume growth rate of tree or stand over some period of time and was calculated using Formula (6) [13,16]:

$$PAIv = \frac{V_E + V_H - V_B}{T_j - T_i} \quad (6)$$

where V_E is the volume at the end of the measurement period; V_H is the average volume that was harvested or died (cut and mortality) across all plots during the same period; V_B is the volume at the beginning of the measurement period; T_i is the year at the beginning of the measurement period; T_j is the year at the end of the measurement period. In this study, we calculated the PAIv of stands between each measurement, with the length of the period being five years.

– The stocking index (w_g) is the ratio of the actual volume of the stand to the model volume estimated using the yield tables (for the same tree species, with the same site index and age):

$$w_g = \frac{V_g}{V_t} \quad (7)$$

where V_g is the actual volume per 1 ha; V_t is the volume per 1 ha estimated using yield tables.

The sample plots were established in oak stands with age varying from 10 to 198 years and the number of trees per hectare ranged from 20 to 2275 (Table 1). The average volume on the sample plots is 218 m^3/ha and the average of PAIv is 6.90 m^3/ha/year (Table 1).

Table 1. Basic characteristics of the sample plots.

Variable	Mean	Minimum	Maximum	Standard Deviation
Predictor Variable				
Age (years)	77.22	10.00	198.00	37.04
Diameter (cm)	32.46	7.06	86.16	15.42
Height (m)	22.06	3.50	38.47	6.97
Density (trees/ha)	632.00	20.00	2275.00	359.79
Volume (m^3/ha)	217.86	0.10	780.90	152.53
Basal area (m^2/ha)	17.14	0.59	47.43	9.09
RSI (%)	20.17	10.33	43.106	5.64
Stocking index	0.84	0.00	2.93	0.55
SDI	718.64	6.48	2479.44	441.04
Dependent Variable				
PAIv (m^3/ha/year)	6.90	0.31	18.39	3.98

2.2. Model Development

This study aimed to develop models explaining the dependence of the PAIv on the characteristics of the stand using a GAM. GAMs provide good predictability and allow analysis of a wide range of data types (qualitative and quantitative) as well as allowing us to determine the importance of the variables and their suitability for the model [24,25,36]. GAMs strike a balance between an interpretable but unbiased linear model and highly flexible "black box" learning algorithms [24,25,36]. GAMs allow us to control the smoothness of prediction functions to prevent overfitting. We can directly solve the bias/variance trade-offs by controlling the swings of the prediction functions [24,25,36].

Variables that can cause multicollinearity were detected by calculating the variance inflation factor (VIF) with helper functions for using "mgcv package" in R (Version 4.2.2, Vienna, Austria) [37]. When the predictors have absolutely no absence of collinearity, the VIF value is 1. In practice, there is usually a collinearity among the predictors. A VIF value that exceeds 5 or 10 indicates a problematic amount of collinearity [38–40]. Variables are evaluated with the VIF function and removed one by one, starting with the highest VIF, until all parameter estimates are significant with VIF at around 5.

The VIF for each variable can be computed using the following formula:

$$VIF_{X_J} = \frac{1}{1 - R^2_{X_J|X_{-J}}} \tag{8}$$

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

The structure of the GAM is:

$$\mathrm{g(E(Y))} = \alpha + \mathrm{s_1(x_1)} + \ldots + \mathrm{s_p(x_p)}$$

where Y is the dependent variable (i.e., what we are trying to predict); E(Y) denotes the expected value; g(Y) denotes the link function that links the expected value to the predictor variables $x_1, \ldots, x_p$; $s_1(x_1), \ldots, s_p(x_p)$ denote smooth, nonparametric functions.

We also used the variable importance plots (vip) function of the "vip package" in R to evaluate the significance of the variables participating in the GAM model [41]. This is a general framework for constructing variable importance plots from various types of machine learning models in R. With vip, there is one consistent interface for computing variable importance for many types of supervised learning models across a number of packages [41]. The selected variables were included in the GAM model for analysis.

In the process of building the GAM model, we used plots, coefficient tables, and the ANOVA function of the "mgcv package" in R to analyze the deviance for the GAM model to determine if any variable is a crucial term to include in the model. The model should only be as complex as necessary to describe the dataset. Therefore, to select the maximum complexity of the model and decide whether to include a given variable in the model, we used ANOVA. The ANOVA function takes the model objects as arguments and returns an ANOVA testing whether a more complex model including an additional variable is significantly better at capturing the data than a simpler model without that variable. If the resulting p-value was sufficiently low (we used the 0.05 level), we concluded that the more complex model is significantly better than the simpler model and thus favor the more complex model. If the p-value was not less than 0.05, we chose the simpler model without the additional variable.

The model performance and possible overfitting in calculating the adjusted R^2 were analyzed by the use of 10-fold cross-validation. In this method, the data were randomly divided into 10 parts. Then, 9 of those parts were used for training and 1 for testing. This procedure was repeated 10 times, each time reserving a different tenth for testing. This method uses all the data for training and validation and also for estimating the prediction error [42,43]. The procedure was performed using the R language packages gam and caret [42,43]. In the last step, we evaluated the performance of the model using:

Mean absolute error(MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{9}$$

Root mean square error(RMSE):

$$RMSE = \sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{n}} \tag{10}$$

Adjusted coefficient of determination:

$$R^2_{adj} = 1 - \left(1 - R^2\right)\frac{n-1}{n-p-1} \tag{11}$$

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

3. Results

Incorporating all of the variables used to describe stand characteristics into the model (Table 2, variable set 1) resulted in high redundancy. The highest redundancy with the other variables was shown by the diameter. When the diameter was excluded (variable set 2), high redundancy was shown by the volume, which was excluded in the next step. In order to develop a model describing the increment, variables for which the VIF was at most around 5 were finally selected (Table 2, variable set 3).

Table 2. Variance inflation factor for each predictor variable considered in the volume increment modeling.

Covariate	Variance Inflation Factor		
	Variable Set 1	Variable Set 2	Variable Set 3
Age	5.70	4.50	4.29
Height	7.64	6.23	5.60
Diameter	8.21	x	x
Volume	6.82	6.55	x
Density	3.31	3.13	2.92
Basal area	1.86	1.84	1.72
Stocking index	5.31	5.02	1.14
RSI	2.03	1.92	1.89
SDI	2.43	2.06	2.03

Examining the significance of the predictor variables indicated their different influence on the PAIv of the oak stands (Figure 2).

Our results showed that the basal area is the most important variable determinant of the PAIv of oak stands. We found that with an increase in the basal area, the PAIv of oak stands substantially increased (Figure 3).

We also found clear overall effects of stand age on the PAIv. Stand age significantly decreased the PAIv of the oak stands. The average PAIv of the oak stands decreased by approximately 1.5 m^3/ha/year every 20 years (Figure 4). However, in stands older than 100 years, the decrease was not so pronounced.

The next important variable determining the PAIv was the height of the oak stands. As the height increased, an increase in the PAIv was observed. The greatest increase in the PAIv was in the range of 25–38 m (Figure 5).

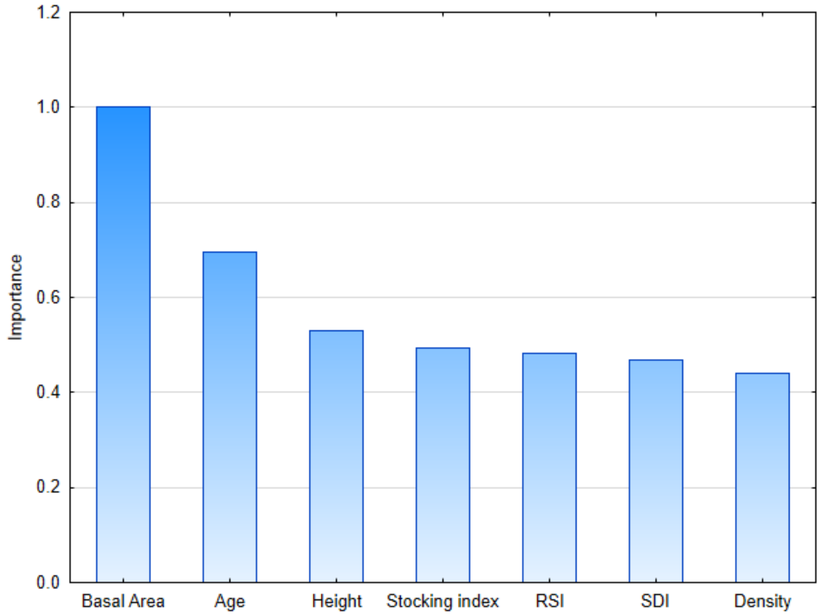

Figure 2. Significance of the predictor variables on the periodic annual volume increment of the oak stands estimated using the variable importance method.

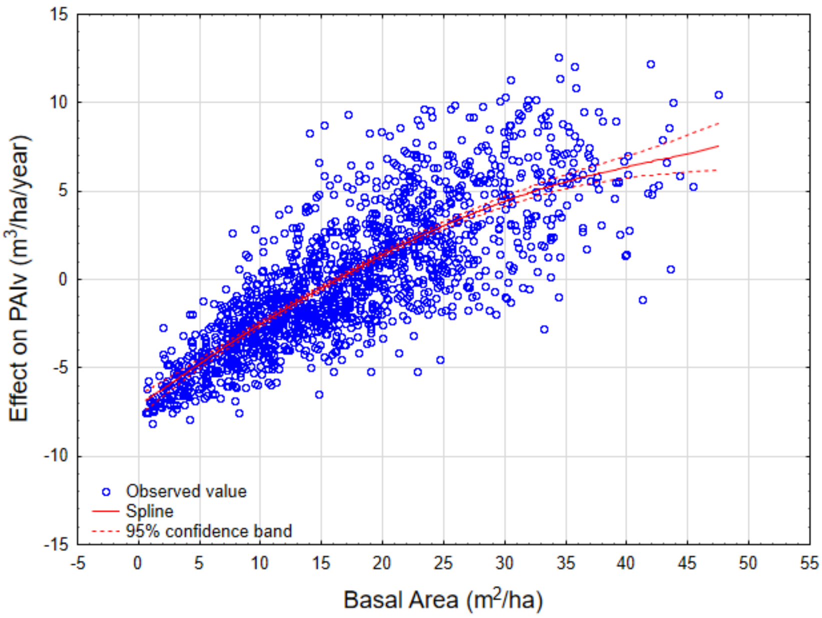

Figure 3. Partial effect of the basal area on the periodic annual volume increment of the oak stands.

Our results also showed slight effects of the stocking index, relative spacing index, stand density index, and density on the PAIv of the oak stands (Figure 6). We found that the fixed-effect stocking index, relative spacing index, stand density index, and density variables were of low significance in the model (Table 3).

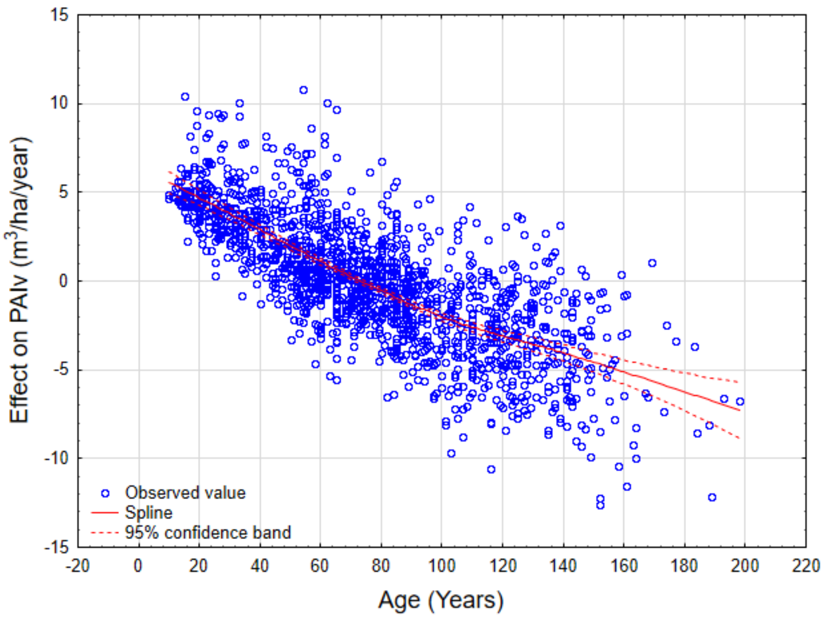

Figure 4. Partial effect of age on the periodic annual volume increment of the oak stands.

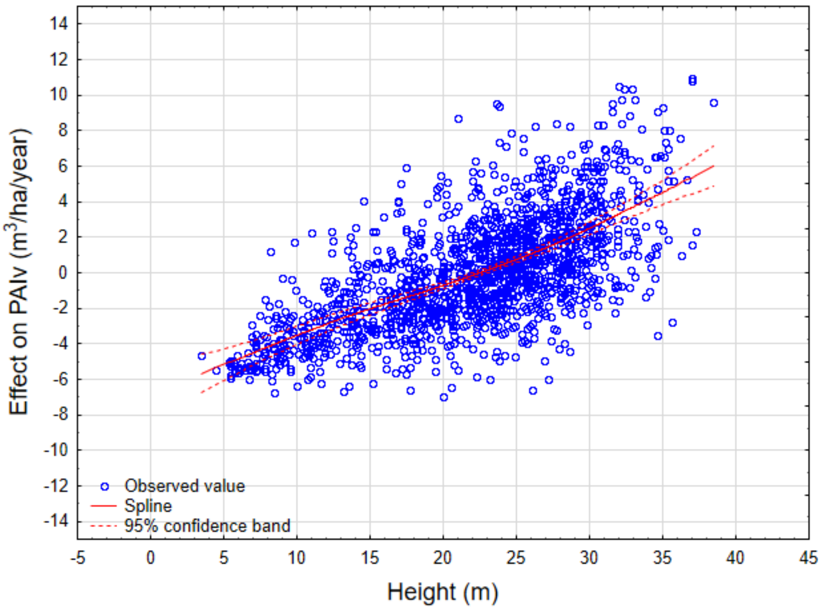

Figure 5. Partial effect of height on the periodic annual volume increment of the oak stands.

Table 3. Approximate significance of seven predictor variables on the periodic annual volume increment described using the GAM model.

Predictor Variable	Effective Degrees of Freedom	Reference Degrees of Freedom	*F*	*p*-Value
Age	4.441	5.511	70.657	<0.0001
Height	2.449	3.168	61.930	<0.0001
Basal area	4.652	5.746	266.957	<0.0001
Relative spacing index	3.904	4.869	2.834	0.0154
Density	1.001	1.002	3.526	0.0608
Stocking index	1.001	1.003	0.779	0.3774
Stand density index	1.796	2.304	0.100	0.8342

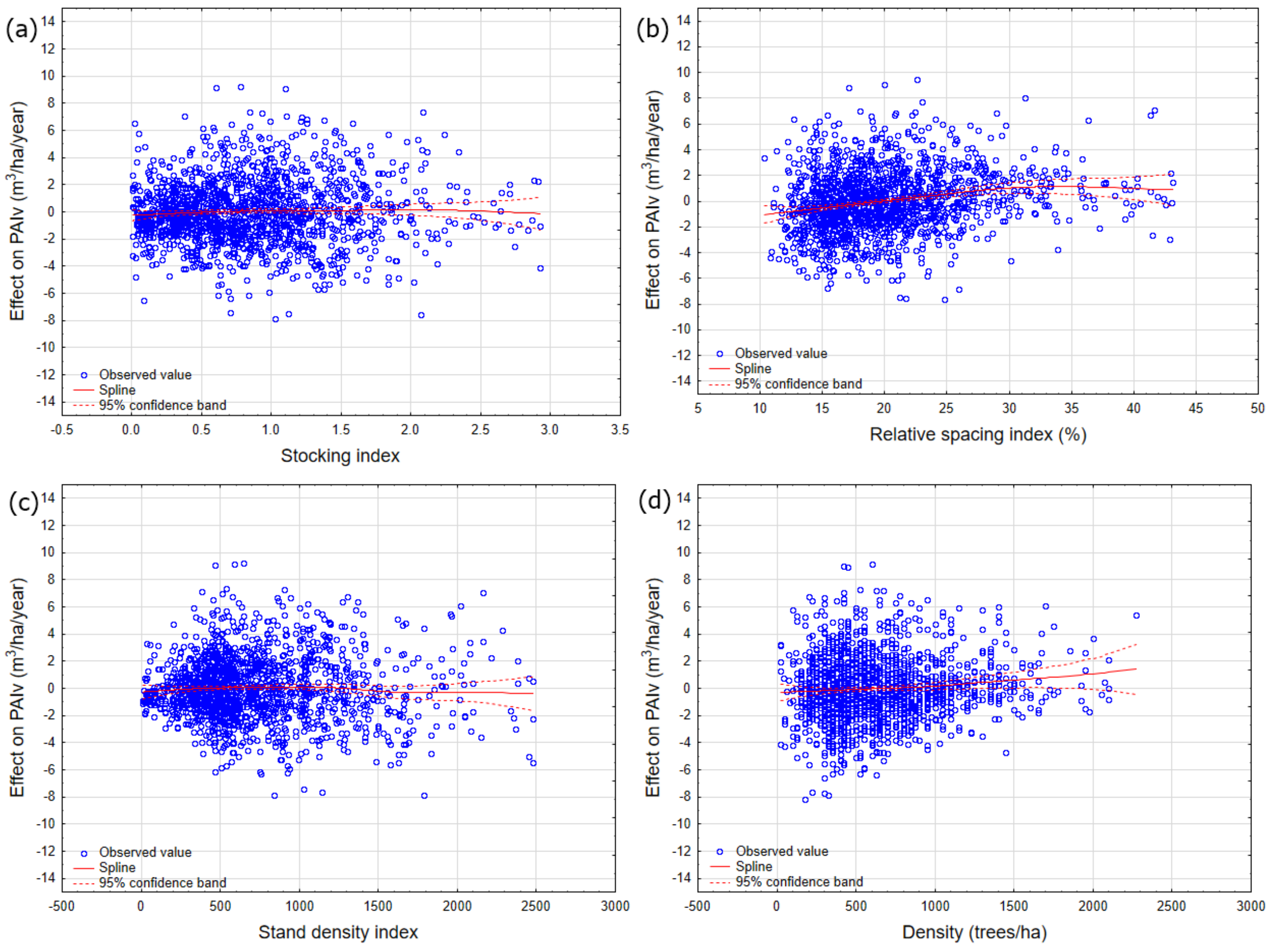

Figure 6. Partial effects of the stocking index (**a**), relative spacing index (**b**), stand density index (**c**), and density (**d**) on the periodic annual volume increment of the oak stands.

In order to test whether the inclusion of variables related to stand density affects growth, a comparison of the simple model with models augmented with the RSI, SDI, stocking index, and density was used. However, using ANOVA of the more complex models that included additional variables describing stand density and of the simpler models without this variable, it was found that the models with the SDI, stocking index, and density variables were not significantly better at capturing the data. Only the addition of the RSI variable significantly increased the predictive ability of the model (ANOVA, $p < 0.05$) (Table 4).

Table 4. Analysis of deviance for the periodic annual volume increment model.

Simple Model (Number)	Extended Model (Number)	F	p
(1) Age, height, basal area	(2) Age, height, basal area, density	2.56	0.0330
	(3) Age, height, basal area, stocking index	0.87	0.3355
	(4) Age, height, basal area, RSI	3.12	0.0079
	(5) Age, height, basal area, SDI	1.77	0.1352
(4) Age, height, basal area, RSI	(6) Age, height, basal area, RSI, density	2.90	0.0766

Our results demonstrated that the model developed with four predictor variables (age, height, basal area, and relative spacing index) can explain approximately 64.6% of the PAIv variability. The mean absolute error of the model (MAE) was 1.80 m^3/ha/year and the root mean square error (RMSE) was 2.35 m^3/ha/year (Table 5). R^2 adj calculated on the basis of 10-fold cross-validation was 61.4%, suggesting model overfitting was not a concern.

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Also the distribution of residuals of the volume increment (Figure 7) indicates the good predictive ability of the developed model.

Table 5. Statistical indicators of the models.

Indicator	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
R^2-adjusted	0.643	0.645	0.643	0.646	0.644	0.646
Root mean square error (m^3/ha/year)	2.37	2.37	2.37	2.35	2.36	2.35
Mean absolute error of the model (m^3/ha/year)	1.82	1.82	1.82	1.80	1.81	1.80

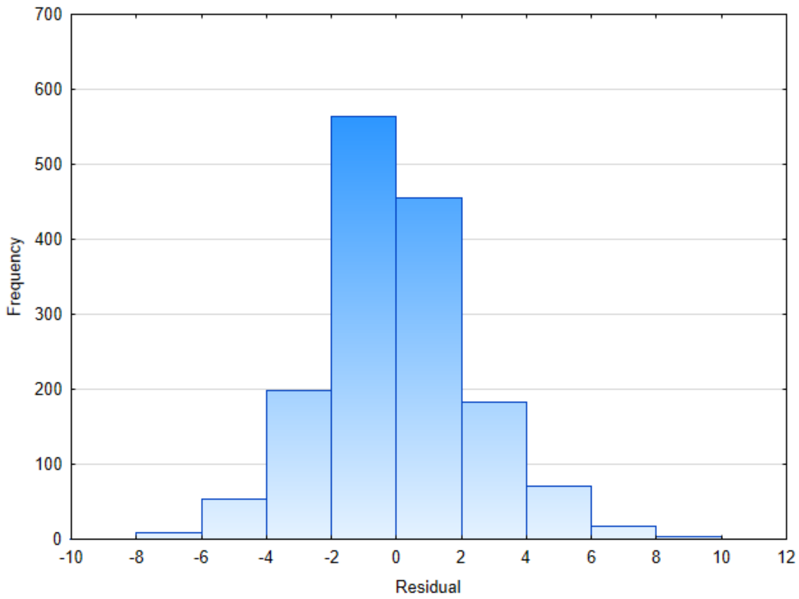

Figure 7. Histogram of the residual values of the model describing the volume increment of oak as the function age, height, basal area, and relative spacing index.

4. Discussion

We identified the most important factors determining the PAIv of oak. This study documented a relationship between the PAIv and the basal area, age, height, and RSI of oak stands. The developed model explained approximately 64.6% of the variance of the PAIv.

Our study showed a strong positive relationship between the basal area and the PAIv of oak stands. We also found that the PAIv of oak stands started to slow down when the basal area increased beyond 30 m^2/ha. This information can be used in forestry practice to determine thinning intensity. The effect of the basal area on the volume increment has been previously reported by other authors. Allen and Burkhart [44] conducted studies on thinning loblolly pine plantations in the southeastern United States. The results-based growth–density relationships suggested that thinned stands can exhibit increased growth at relatively lower densities compared to that of an un-thinned stand on a similar site [44]. Hamidi et al. [2] demonstrated that the basal area is the most important predictor value for estimating the annual volume increment in uneven-aged mixed forests. A study on spruce plantations in Norway showed that the volume increment increases with increasing basal area up to the maximum basal area of a given site [45]. Another study in the Boreal Forest Natural Region of Alberta, Canada, also indicated a significant positive relationship between the volume increment and the basal area of white spruce stands [46]. The basal area is a useful index to help forest managers take appropriate silvicultural measures. From the point of view of the intensification of timber production in the case of oak stands, it is therefore advantageous to maintain a relatively large (30 m^2/ha) basal area, which can be achieved by, among other things, less intensive silvicultural treatments. However, the problem of stand stability must be taken into account when planning treatments. This is because a high basal area leads to an increase in the slenderness and shortening of tree crowns, which can have an adverse effect on wind risk and the condition of individual trees.

Besides the basal area, we verified the significance of the RSI for the PAIv of oak stands. Saud et al. [47] used the RSI as a predictor in the growth model, showing that a quality nonlinear model with minimum information loss can be obtained. Our results showed a proportional relationship between the RSI and PAIv of oak stands; however, when the RSI value exceeded 30%, it hardly affected the PAIv anymore. Another study documented the effectiveness of using the RSI to determine thinning schedules and delineate indirectly derived survival patterns over time for young loblolly pine plantations [48]. A study by Socha et al. using NFI data for Scots pine in Poland also demonstrated a strong correlation between the RSI and volume of stands [35]. Relative spacing is therefore a measure of crowding and competition in stands, relating well to a stand's growth rate, canopy depth, and self-thinning capacity [34,35]. Relative spacing is an indicator that can be quantified and predicted in the future. Thus, it is essential for planning and determining when to take future management actions for stands.

Our results confirmed the high significance of age for the PAIv, which is in line with other studies on the effect of age on the growth increment. These results could be explained by trees undergoing physiological changes as they age, including lower rates of photosynthesis, reduced efficiency in transporting water, and shifting carbon sources to different parts of the tree [49–54]. Yang et al. [55], through regression analysis, proved that forest age is one of the most important factors affecting growth. Research conducted in a primary forest in Heilongjiang province, northeastern China, found that forests have a faster growth rate at a young age and decrease after reaching a maximum [56]. Another study in the eastern United States demonstrated that black oak in older age classes grows much more slowly than younger black oak throughout the lives of these older trees [54]. The results of a study on oak forests in the Eastern Carpathians also showed similar results for the decline in biomass with age [57]. A study in mixed stands (pine/oak) in the Netherlands noticed a decline in the PAIv with age in each species [58]. Moreover, Stimm et al. [59] showed that the stand age variable has a negative effect on the PAIv of oak in both monospecific and mixed oak stands (*Quercus petraea* and *Quercus robur*). The high importance of age for the PAIv should be an important guideline in forest management for optimization the potential of forests for timber production. However, the inhibition of the PAIv should also be an important signal in the context of exploiting the potential of forests for climate change mitigation and carbon sequestration in forest ecosystems.

Tree height is the most dynamic biometric features due to its sensitivity to the environmental changes and silvicultural treatments. The volume increment varies depending on the tree height and height increment [7,9,20,60,61]. Our results demonstrated a positive relationship between height and the PAIv. In forest management practice, information about stand height is often used due to the facility of data collection and high accuracy under application of modern methods [51,62–64]. Therefore, stand height can be commonly used as a good proxy for predicting the PAIv. RSI and stand height can be determined using remote sensing data such as airborne laser scanning point clouds [35]. Therefore, the relationship of volume increment with RSI and stand height documented in our study can be used in the remote sensing determination of volume increment of oak stands. In addition, the change in height growth trends is a good indicator of the effect of climatic and environmental changes on forest conditions. Thus, establishing a relationship between height and the PAIv can provide additional insight into the importance of climatic and environmental factors in shaping tree growth.

In addition to the basal area and RSI indicators, researchers also use other indicators to assess the competition level of the trees in a stand. A study on Norway spruce and European beech proved a relationship between the SDI and periodic annual increment. When the SDI is reduced in young stands, periodic annual increment follows a unimodal curve, while in older stands, it follows an increasing pattern [65]. Allen and Burkhart [44] showed that the relationship between the periodic annual increment and SDI increases at low to mid-densities, but the benefits of increasing density gradually decrease at higher densities. Another study using Spanish NFI data demonstrated that the maximum volume increment of oak occurs at the maximum stocking index [66]. In our study, we also evaluated the effect of density, SDI, and stocking index on the PAIv of oak stands. Our analyses showed that when the RSI is included, the SDI does not increase the significance of the model, so the SDI was excluded from the final version of the model.

The influence of tree characteristics on periodic annual tree increment trends is useful for understanding stand growth. Knowing the contribution of each factor to the size of the PAIv during tree development provides information for silvicultural work to stimulate the volume increment. In our study, we did not analyze factors related to site or climate, which can also significantly affect the PAIv. Toledo et al. [11] showed that climate is the most vital driver affecting volume growth and has significant consequences for forest productivity. Baribault et al. [67] demonstrated that volume growth is also affected by irradiance, soil fertility, and topography. Therefore, future research on oak volume increment should be expanded to include analyses that additionally take into account environmental factors and genetic variation.

5. Conclusions

We documented the effect of age, height, basal area, and RSI on the PAIv of oaks in Poland. The PAIv of oaks decreased gradually as the tree aged. The dependence of the PAIv on stand density was also shown through its relationship with the basal area and RSI. The results of the study may be helpful in determining the intensity and frequency of silvicultural treatments in oak stands in order to achieve the optimal level of volume increment through appropriate regulation of basal area and density in relation to stand height and age. The volume increment of stands is one of the most important indicators of forest dynamics. The possibility of modeling the volume increment allows for forecasting forest development and is important in determining wood and biomass production and the potential for CO_2 sequestration by forest ecosystems. Therefore, identifying how individual stand factors influence the volume increment is crucial in sustainable forest management.

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ORIGINAL PAPER

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

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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*.,

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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,

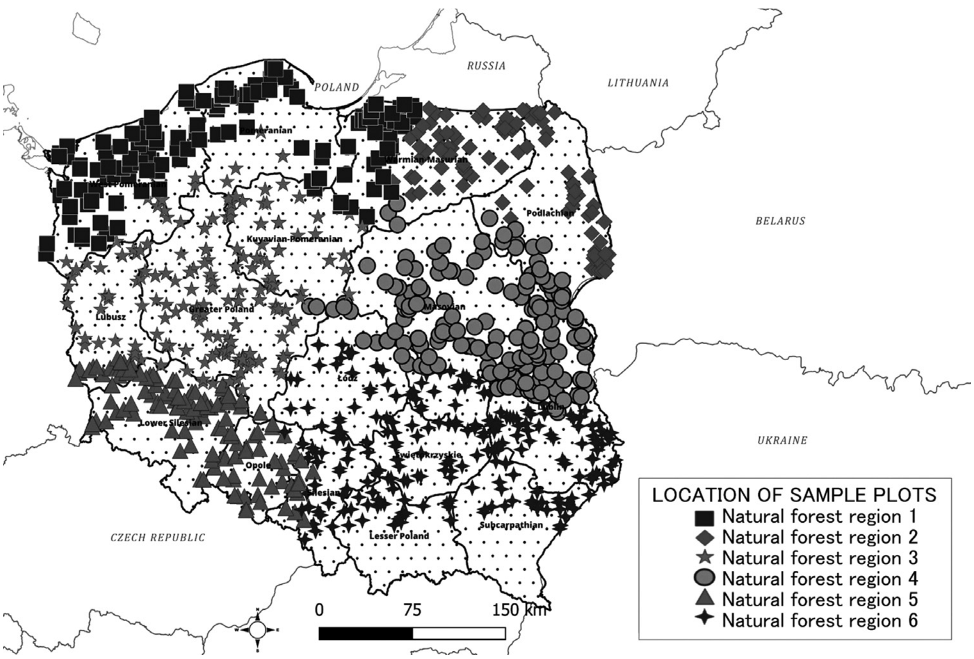


Fig. 1.
Location of NFI oak-dominated sample plots in Poland

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 geo-logy	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).

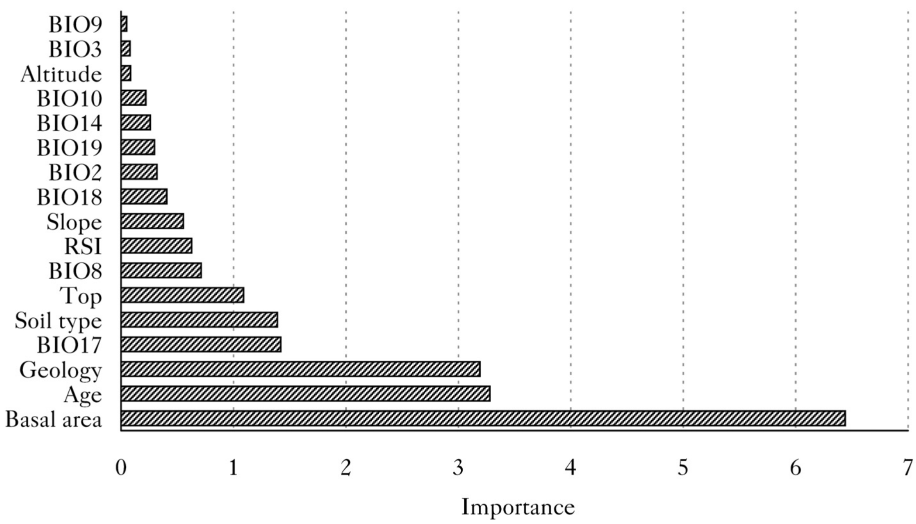


Fig. 2.
Significance of the predictor variables on the periodic annual volume increment of the oak stands

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

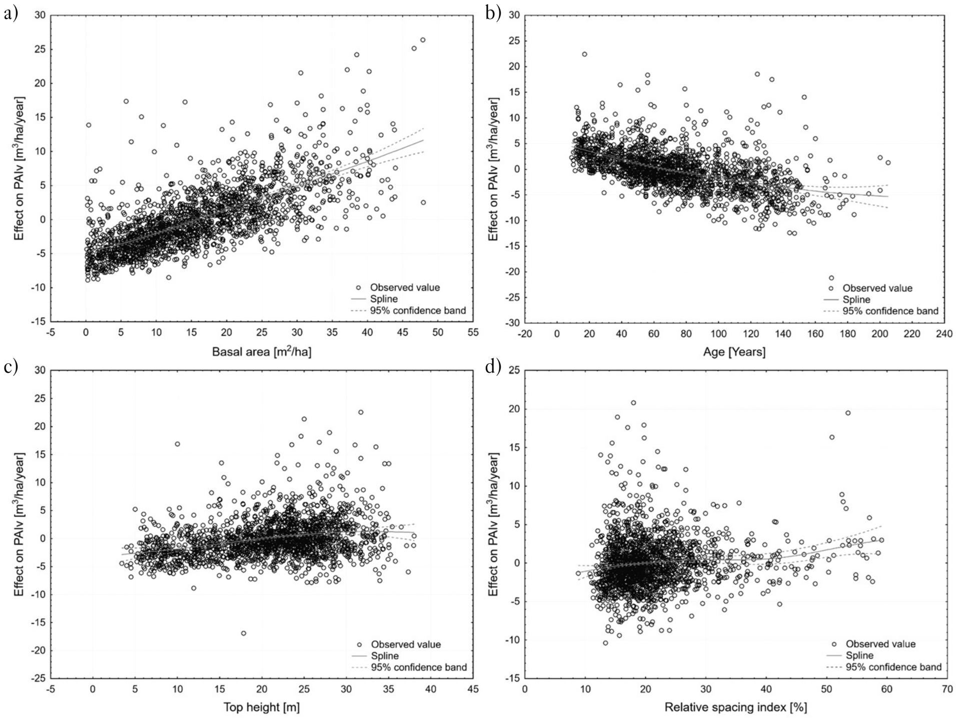
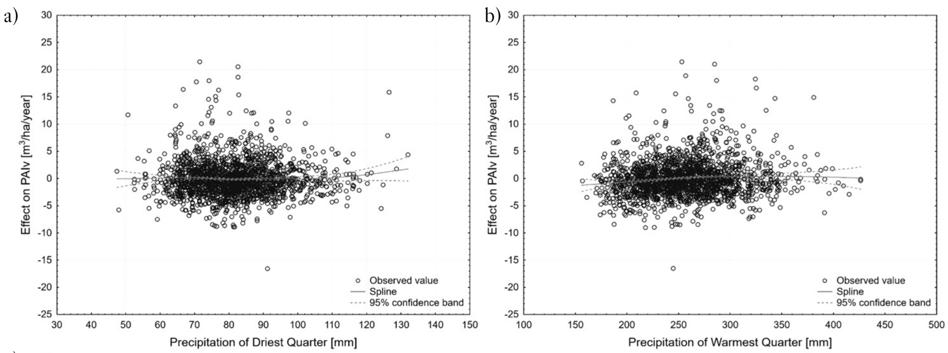


Fig. 3.

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



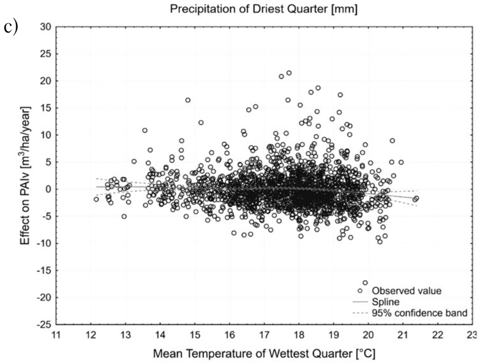


Fig. 4.

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).

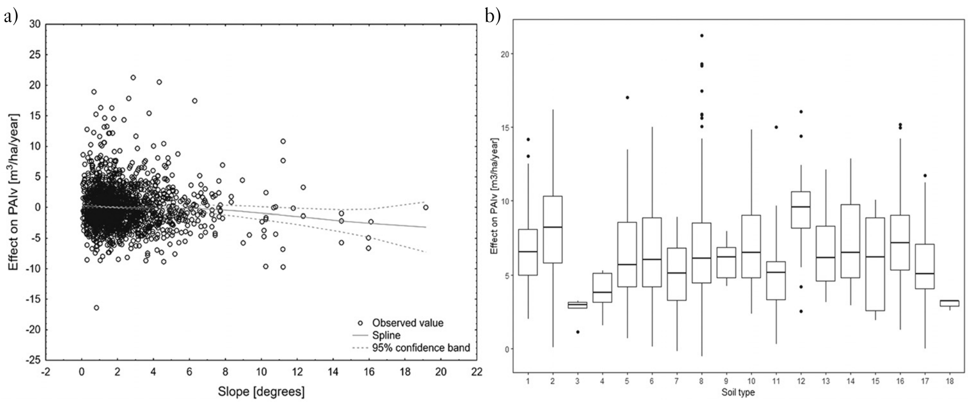


Fig. 5.
Partial effect of slope (a) and soil type (b) on the periodic annual volume increment of the oak stands (Soil type information in Table 2)

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

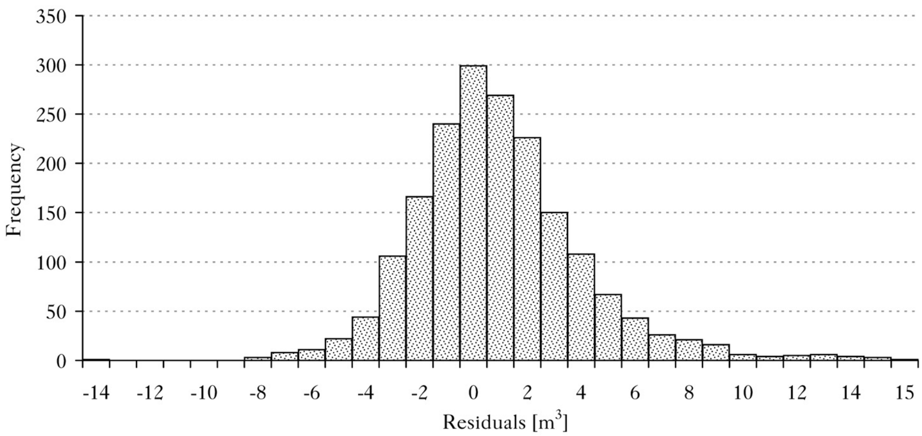


Fig. 6.
Histogram of the residual values of the GAM model

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.

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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.

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