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Drivers of site productivity for oak in Poland

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.

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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):

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

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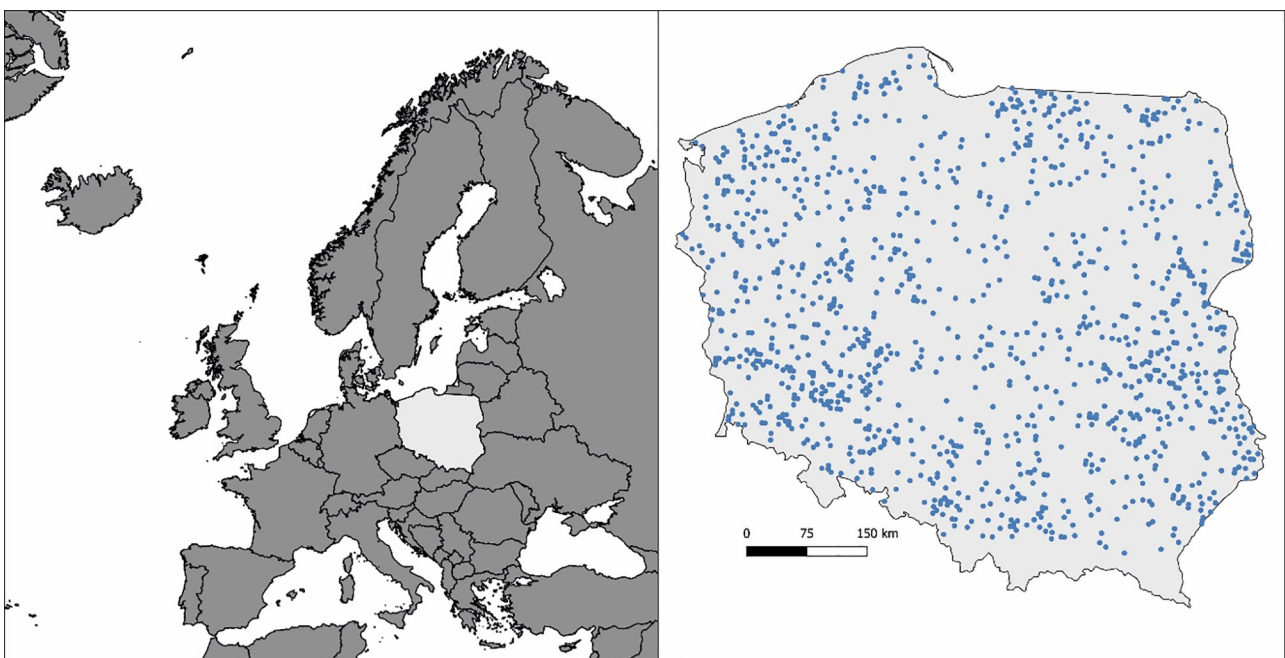
Fig. 1. Location of 2490 NFI oak dominated sample plots (blue dots) in Poland

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

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

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

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

(Socha et al., 2020) based on the dynamic Korf equation (Anta et al., 2006) describing change in the TH with age (equation 3).

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

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 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.
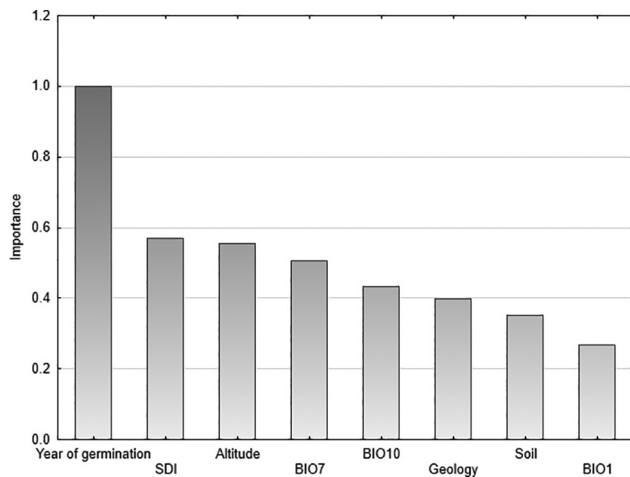

Fig. 2. Important variables for developing the GAM model

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).
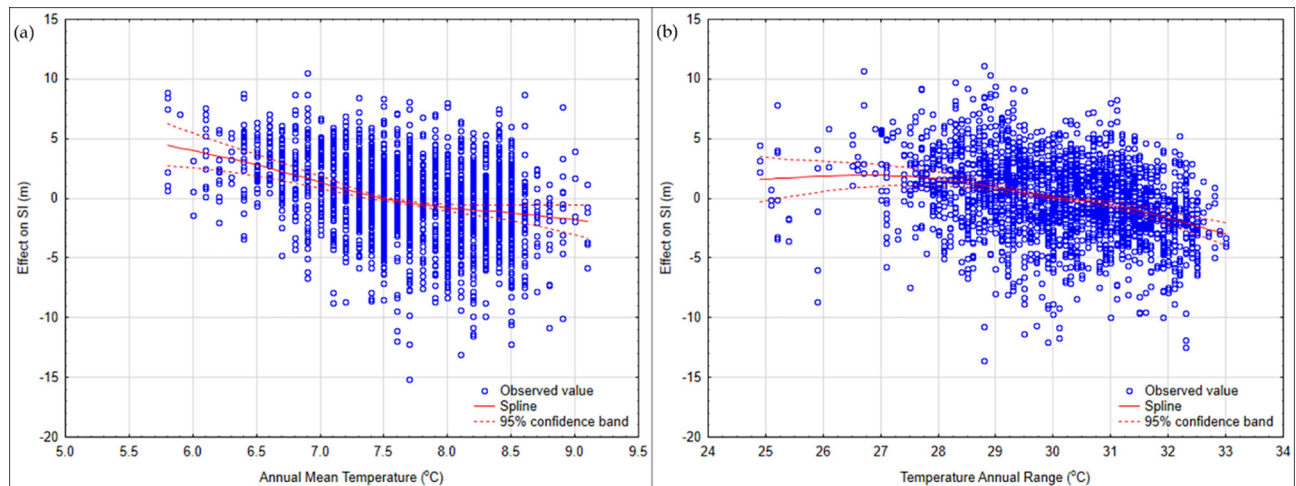

Fig. 3. Partial effects of the annual mean temperature (a) temperature annual range (b) on the site index for oak

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,
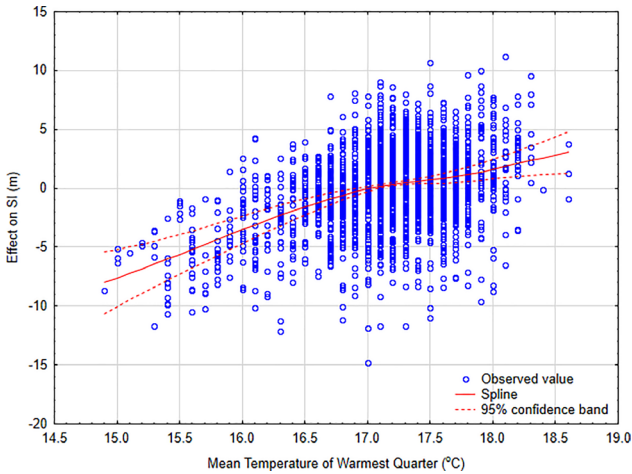
a further increase of altitude had almost no effect on SI (Fig. 5).

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

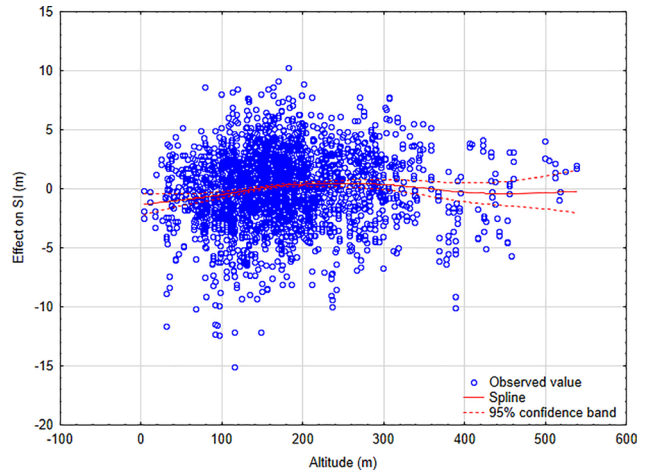Fig. 5. Partial effects of altitude on the site index for oak

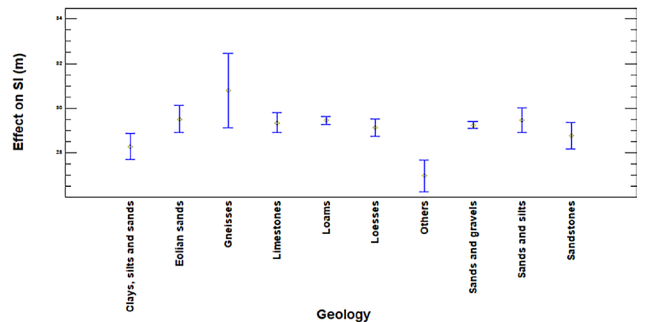Fig. 6. Partial effects of soil type on the site index for oak

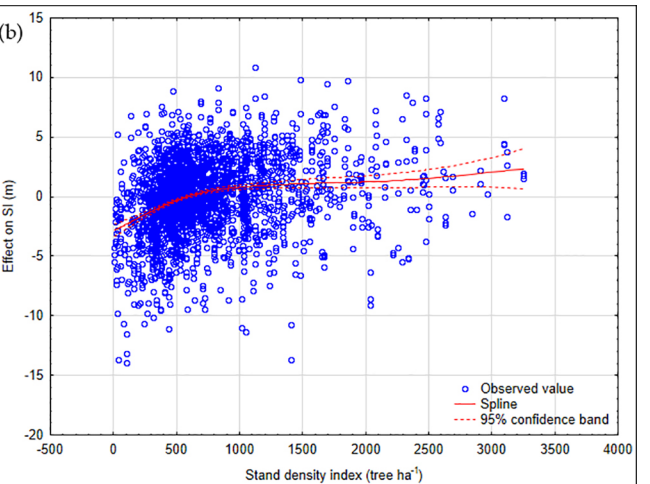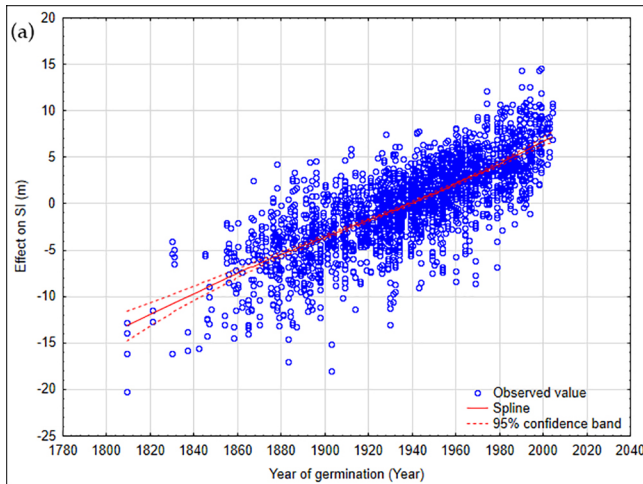Fig. 7. Partial effects of geology type on the site index for oak

Fig. 8. Partial effects of year of germination (a) and stand density index (b) on the site index for oak
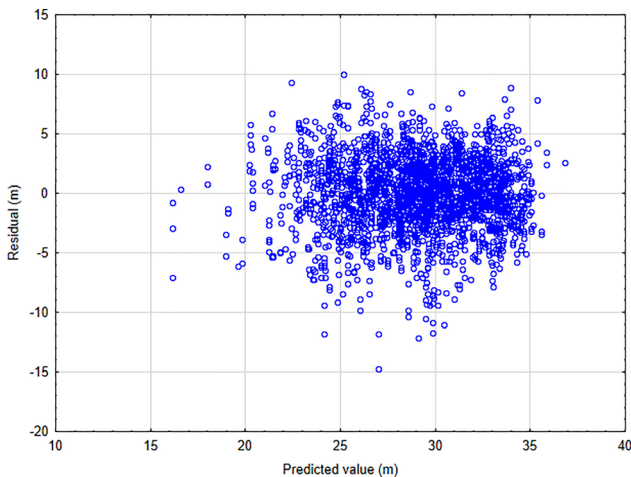
Fig. 9. Residual SI versus values predicted by the developed GAM model for oak

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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