BALTIC FORESTRY

http://www.balticforestry.mi.lt
ISSN 1392-1355
eISSN 2029-9230

Baltic Forestry 2021 27(1): 157–165
Category: research article
https://doi.org/10.46490/BF542

The use of measurable traits of trunk and crown to assess the biosocial classes of oak trees (*Quercus robur* L.)

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Zawieja, B., Turczański, K., Najgrakowski, T. and Kaźmierczak, K. 2021. The use of measurable traits of trunk and crown to assess the biosocial classes of oak trees (*Quercus robur* L.) *Baltic Forestry* 27(1): 157–165. https://doi.org/10.46490/BF542.

Received 25 November 2020 **Revised** 9 June 2021 **Accepted** 18 June 2021

Abstract

The crown class assessment is a key element in forestry practice. It is a traditional method that finds application in thinning plans, assessment of site index, tree competition, or crown condition. Assigning trees into a given class is done during field surveys and requires precision and experience to avoid inaccuracy. Therefore, Kraft's system has often been criticized and modified. Thus, in our study, we aimed to analyse whether the directly measured traits of trunk and crown of oak trees (*Quercus robur* L.) can be applied to crown class assessment. For this purpose, we used the principal component analysis (PCA) and nonlinear kernel principal component analysis (KPCA) based on measurable traits of trunk and crown, i.e., the height of the tree, the diameter at breast height, the length of the crown, and the field crown projection area. In total, we measured 286 mature trees in three oak stands located in western Poland. Results indicate that all chosen traits of trunk and crown allowed, though not always perfect, to assign the trees into given crown classes. The greatest contribution to crown class distinction had the diameter at breast height and the parameters of crown, i.e., and the field crown projection area. Furthermore, results show that the best method of assigning the trees into biosocial classes is the KPCA Gauss, considering the percentage explanation of the total variability, and KPCA Laplace, considering the visual division. In the latter, the multivariate analysis resulted in a similar crown class assignment as the field-assigned method. However, its application requires measurements that make it neither cheaper nor faster than a traditional crown class assessment. It indicates that a traditional field-assigned method, despite its subjectivity, should continue to be of great importance in forestry practice. Moreover, the alternative traits of trunk and crown can be a potentially useful statistical substitute for crown class assessment.

Keywords: crown class, oak stand, trunk and crown traits, multivariate methods

Introduction

Light availability is a key component in forest ecosystems. It is often the limiting factor in the survival of trees or their growth in both hardwood forests and tropical rainforests (Kunstler et al. 2009, Sterck et al. 2013). Moreover, competition for light causes different strategies of trees to space-filling manifested in terms of its growth dynamics, height, diameter at breast height (DBH), crown size, and morphology (Pretzsch 2014). Kraft (1884) used knowledge of such adaptation to divide trees into classes due to their social position in the stand. Crown classes are originally devised for pure even-aged stands or those composed of species with the same height regimes (Smith et al. 1997) and can define thinning type, its intensity, site index (Husch et al. 1982), tree mortality, succession patterns, tree competition (Ward and Stephens 1993) or leaf area distribution (Gilmore and Seymour 1997).

Trees are classified according to their heights, position in the forest stand, and crown morphology (Burschel and Huss 1997). This approach allows grouping the trees of the same 'energy growth' (Kraft 1884). There are (I) predominant trees – clearly higher than the surrounding trees visibly protruding above the general level of the canopy, with strongly developed crowns; (II) dominant trees – forming the general upper level of the canopy with relatively well-developed crowns; (III) codominant trees – slightly lower than the prevailing, with clearly less developed crowns and the side confining; (IV) dominated trees – significantly lower than the general level of the canopy, overshadowed with a badly shaped confining crowns and free tops in the middle storey; (V) suppressed trees – completely overtopped with alive (shade-tolerant trees), dying or dead crowns (Kraft 1884, Burschel and Huss 1997). Trees of the I–III class compose the so-called dominant stand whilst those of class IV and V the dominated stand (Jaworski 2004).

Tree crown position as it relates to dominance in the forest stand varies slightly in accordance with different monitoring methods. Smith et al. (1997) distinguished, after Kraft, dominant, codominant, intermediate, and suppressed trees. Dominant and codominant trees are the largest trees and form the general level of the stand canopy. Intermediate and suppressed trees are the smallest trees and generally are overtopped by dominant and codominant trees (Smith et al. 1997). According to International Co-operative Programme on Assessment and Monitoring of Air Pollution Effects on Forests, social status assessment is determined using five classes: dominant, codominant, subdominant, suppressed, and dying trees (Eichhorn et al. 2010). Other systems developed, i.e. from tending methods of selective thinning (Rittershofer 1999, Röhrig et al. 2006).

Practical difficulties in biosocial class assessment come from its subjective estimation. That is why Kraft's system has often been criticized and modified. Assigning trees into a given class is done in the forest and its accuracy depends on human experience and judgments rather than on strict values. That is why many attempts have been done to improve it. Excluding modified Kraft's systems, the attempts concerned statistical methods based on different tree traits. These traits are directly correlated with the biosocial position of tree. Bechtold (2003) replaced crown class with two alternatives, more repeatable, variables – crown position and crown light exposure. Nigh and Love (2004) used the diameter at breast height, the height of tree, and the length of the crown together with light model tRAYci to predict crown classes. Similar traits with additional variables such as slenderness, height increment, tree basal area, and field crown projection area were also tested in the linear discriminant analysis (LDA) and nonlinear kernel discriminant analysis (NKDA) (Zawieja and Kaźmierczak 2015, 2016, Kaźmierczak and Zawieja 2016). However, those analyses required prior knowledge of crown classes at least for a sample group.

Presented literature indicates that traditional assessment of crown classes (hereinafter referred to as the field-assigned method) depends on human accuracy and judgments. It also suggests that it can be replaced by statistical methods based on different tree features. Thus, in our study, we aimed to analyse whether the directly measured traits of trunk and crown of oak trees (*Quercus robur* L.) can be applied to crown class assessment. Among all tested features, we selected those strictly connected with the biosocial position of the tree and those frequently measured during the forest surveys, i.e. the height of the tree, the diameter at breast height, the length of the crown, and the field crown projection area. For this purpose, we used multivariate methods that do not require prior knowledge of field-assigned crown classes. We assumed it will allow us to assign the trees into crown classes both in plots with and without *a priori* known biosocial position. Our study expands the results of previously conducted research, i.e. by Bechtold (2003), Nigh and Love (2004), and Kaźmierczak and Zawieja (2016). It also brings a new light to forestry practice as the crown class assessment is of great importance in silviculture.

Material and methods

Study plots

We conducted our research using the data from three study plots established in three separate oak stands (*Q. robur* L.). The first plot with an area of 0.75 ha represented a 135-year-old oak stand in a moderately moist broadleaved forest (1). The second plot (0.25 ha) was established in a 97-year-old oak stand in a mesic mixed broadleaved forest (2). The third plot (0.10 ha) was established in a 100-year-old stand in a mesic mixed broadleaved forest (3). In total, we measured 286 oak trees: 152 (1), 84 (2), 50 (3). The stands were situated in Zielonka Experimental Forest District (1 and 2) and Piaski Forest District (3), western Poland.

Study design

Within all three plots, we measured the height of trees (H) and the heights of live crown basis (CBH) using a Suunto altimeter, with 0.1 m accuracy; the diameter at breast height (DBH) was measured based on two measurements taken along the cardinal directions N-S and W-E and pooled out as arithmetic mean with 0.1 cm accuracy; the length of the crown (CL) was calculated as a difference between tree height (H) and the height of live crown basis (CBH); and field crown projection area (CPA) as a polygonal area with projections of characteristic points of the crown assessed with a mirror-based crown projector. The CPA was calculated using a polar method (Lemke 1966).

The basic values of measured traits, i.e. mean, maximum and minimum values (min–max), and standard deviation (*SD*), we collated in Tables 1–3. Moreover, within two stands (plots 1 and 2; Tables 1–2) we used the traditional field-assigned method to visually assess the crown classes after Kraft (1884).

Table 1. Basic values of measured traits within the 135-year-old oak stand (plot 1)

Crown class	No. of trees	Mean ± *SD* (min–max)			
		DBH	H	CL	CPA
I	11	59.04 ± 6.28 (47.30–65.90)	32.27 ± 1.31 (29.70–34.60)	15.16 ± 2.41 (12.10–18.40)	103.72 ± 26.74 (61.94–139.06)
II	100	44.15 ± 7.12 (31.15–65.00)	30.01 ± 1.33 (25.40–33.30)	11.20 ± 2.24 (6.50–15.90)	37.38 ± 17.52 (7.25–95.50)
III	26	35.10 ± 6.52 (25.95–51.05)	26.37 ± 1.35 (22.50–28.40)	8.48 ± 1.75 (4.30–11.10)	23.06 ± 11.55 (7.40–49.56)
IV	15	21.20 ± 4.08 (12.10–26.45)	19.91 ± 3.98 (11.50–24.70)	6.23 ± 2.04 (2.30–9.30)	15.64 ± 7.78 (2.21–30.54)
All	152	41.41 ± 10.93 (12.10–65.90)	28.55 ± 3.70 (11.50–34.60)	10.53 ± 3.00 (2.30–18.40)	37.58 ± 26.06 (2.21–139.06)

Table 2. Basic values of measured traits within the 97-year-old oak stand (plot 2)

Crown class	No. of trees	Mean ± *SD* (min–max)			
		DBH	H	CL	CPA
I	9	34.78 ± 2.35 (31.75–39.50)	23.78 ± 0.71 (22.30–24.50)	8.11 ± 1.92 (5.20–11.40)	21.69 ± 4.15 (14.45–26.43)
II	55	31.17 ± 5.28 (21.25.0–45.0)	23.27 ± 1.49 (19.20–26.00)	6.59 ± 2.09 (2.70–11.40)	15.17 ± 6.79 (2.79–32.96)
III	15	23.20 ± 4.43 (14.75–32.25)	21.02 ± 2.39 (18.10–24.40)	5.67 ± 1.62 (3.60–9.10)	7.35 ± 2.94 (2.95–13.51)
IV	5	14.00 ± 0.79 (12.75–14.75)	16.00 ± 1.32 (13.90–17.40)	3.60 ± 0.77 (2.60–4.40)	5.31 ± 2.36 (1.64–7.53)
All	84	29.11 ± 6.95 (12.75–45.00)	22.49 ± 2.46 (13.90–26.00)	6.41 ± 2.14 (2.60–11.40)	13.88 ± 7.29 (1.64–32.96)

Table 3. Basic values of measured traits within the 100-year-old oak stand (plot 3)

No. of trees	Mean ± *SD* (min–max)			
	DBH	H	CL	CPA
50	37.52 ± 5.42 (28.60–52.30)	24.54 ± 3.03 (17.80–30.80)	13.25 ± 4.01 (4.70–23.30)	35.12 ± 17.45 (7.36–88.93)

Data analysis

In our study we used two multivariate methods to assign the trees into Kraft's classes, i.e. the principal component analysis, PCA (Krzanowski 2000, Krzyśko 2009) and nonlinear kernel principal component analysis, KPCA (Schölkopf et al. 1997, 1998, Wang 2012). The analyses were based on measurable traits of trunk and crown (H, DBH, CL, and CPA).

The main aim of the PCA analysis is the reduction of dimensionality while maintaining most of the total variability of analysed traits. As a result, new variables are created which constitute a linear combination of all the traits. The coefficients of the linear equations are determined to maximize the variance of successive components (PCs). Hence, PC1 explains the largest part of the variance, PC2 the largest part of the remaining variance, etc. Consequently, the sum of the variances of all PCs equals the sum of the variances of all the traits. The absolute values of the coefficients of individual linear equations present the contribution of a given trait to the main component. Hence, if the equation below is the *i*-th principal component (PC*i*), i.e.

$$\mathrm{PC}i = a_{1i}\mathrm{H} + a_{2i}\mathrm{DBH} + a_{3i}\mathrm{CL} + a_{4i}\mathrm{CPA}\,, \qquad (1)$$

then $|a_{1i}|$ it means the contribution of the height to PC*i* etc.

For analysis, we have chosen the first two PCs which together explained the highest percentage of the total variability. The results that we presented in biplots (Figures 1–3, see also Table 4) show the objects in the form of points in the new coordinate system PC1 and PC2, and traits (H, DBH, CL, and CPA) as vectors, which length was determined by the coefficients from equation (1). The analysis of biplots shows the contribution of the individual traits to the arrangement of points on the chart. To perform the PCA analysis, we standardized the original data separately for each trait.

In the KPCA analysis we also standardized data and then we determined the kernel matrix using different kernel functions, i.e. Chi-squared $k(\mathbf{x},\mathbf{y}) = 1 - \sum_{i=1}^{n} \frac{2(x_i - y_i)^2}{(x_i + y_i)}$, Laplace $k(\mathbf{x},\mathbf{y}) = \exp(-\sigma\|\mathbf{x}-\mathbf{y}\|)$ ($\sigma > 0$), and Gauss $k(\mathbf{x},\mathbf{y}) = \exp(-\sigma\|\mathbf{x}-\mathbf{y}\|^2)$. Then, for transformed data, we performed the usual principal component analysis (Deręgowski and Krzyśko 2014) (Figures 1–3).

The PCA and KPCA analyses reduced the multidimensionality represented by the values of H, DBH, CL, and CPA into two dimensions that allow visually dividing the data into groups, i.e. subsequently separated by dashed lines into biosocial classes (Figures 1–3). Next, we determined the erroneous probabilities allowing us to choose functions presenting the division of trees into crown classes closest to the original assessment. As Kraft's classes for the third plot were not field-assigned, therefore, the probability of incorrect classification cannot be determined.

Additionally, we prepared "matchstick" charts (own idea) as a model that visually determines the proportions of trees assigned to different Kraft's classes in all three plots.

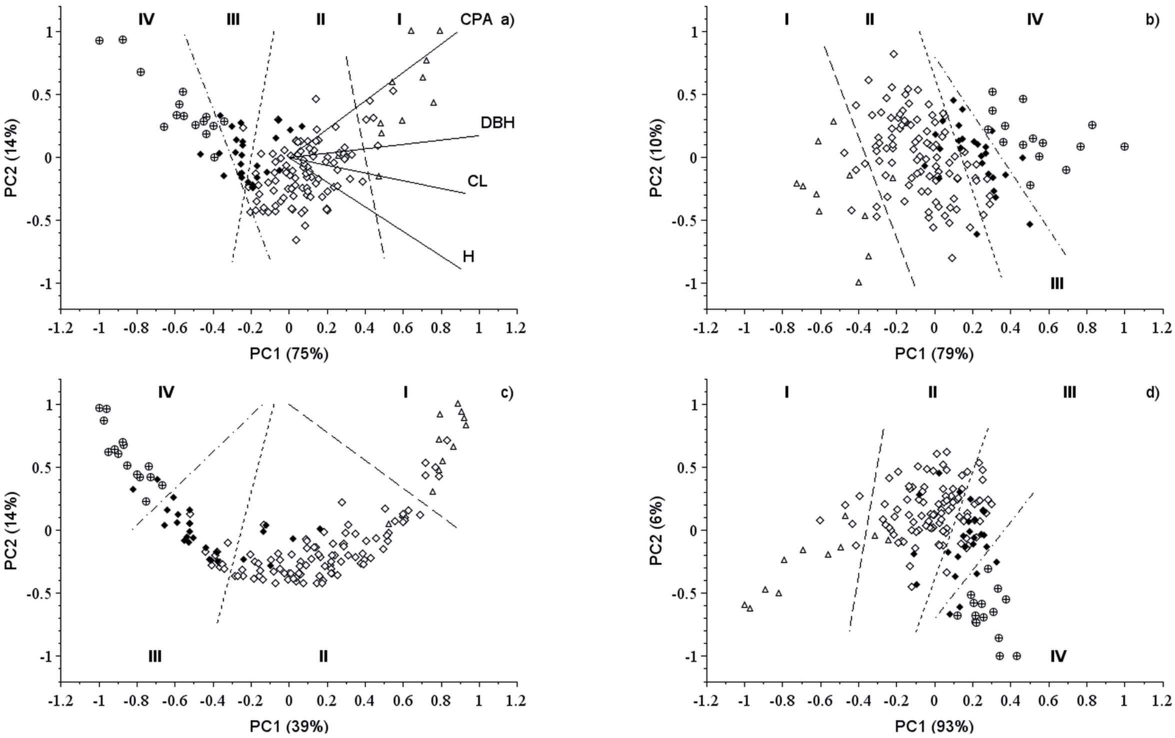


Figure 1. The PCA and KPCA biplots for the first plot

Each symbol stands for a separate crown class: Δ – I class, ◇ – II class, ◆ – III class, and ⊗ – IV class. Crown classes are also separated by dashed lines. Each graph corresponds to a given analysis: a) PCA, b) KPCA Chi-squared, c) KPCA Laplace, d) KPCA Gauss.

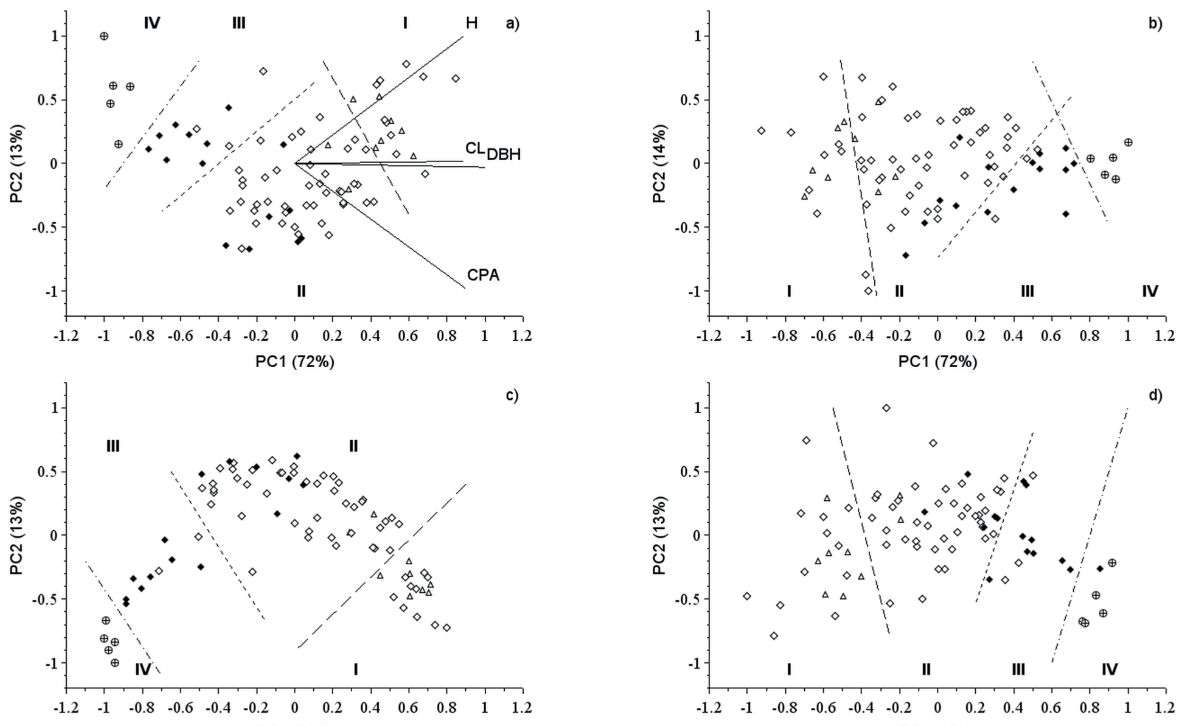


Figure 2. The PCA and KPCA biplots for the second plot

Each symbol stands for a separate crown class (similarly to Figure 2): Δ – I class, ◇ – II class, ◆ – III class, and ⊗ – IV class. Crown classes are also separated by dashed lines. Each graph corresponds to a given analysis: a) PCA, b) KPCA Chi-squared, c) KPCA Laplace, d) KPCA Gauss.

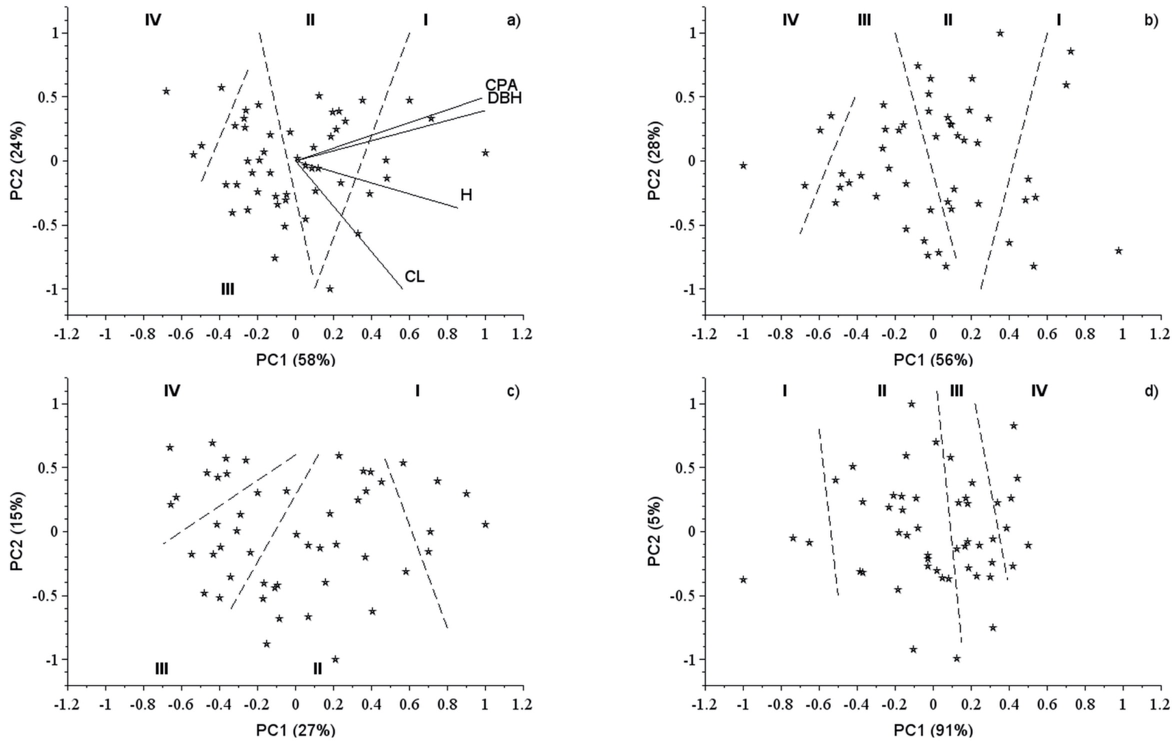


Figure 3. The PCA and KPCA biplots for the third plot

Crown classes are separated by dashed lines. Each graph corresponds to a given analysis: a) PCA, b) KPCA Chi-squared, c) KPCA Laplace, d) KPCA Gauss.

Table 4. Contribution of traits to PCs in the PCA analysis

	The first plot				The second plot				The third plot			
	DBH	H	CL	CPA	DBH	H	CL	CPA	DBH	H	CL	CPA
PC1	0.94	0.84	0.87	0.83	0.92	0.82	0.83	0.82	0.87	0.75	0.49	0.86
PC2	0.09	–0.47	–0.15	0.53	–0.01	0.51	0.01	–0.49	0.31	–0.29	–0.79	0.39

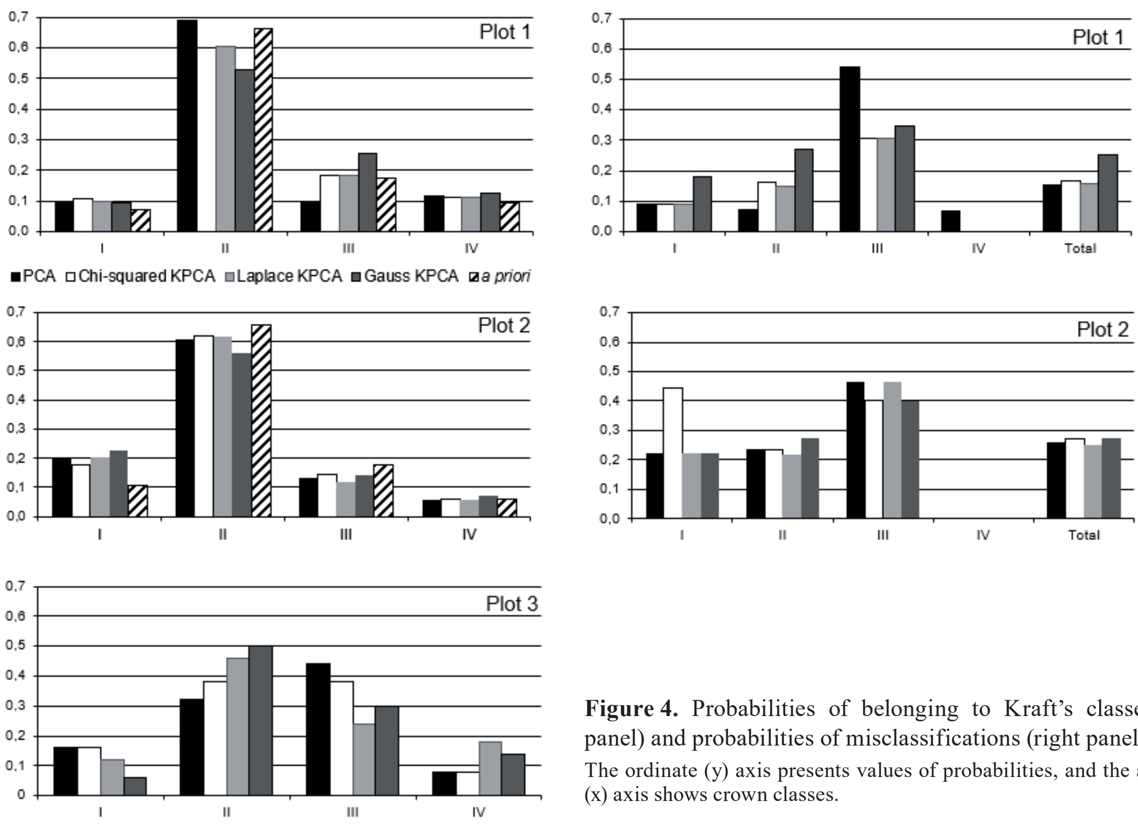
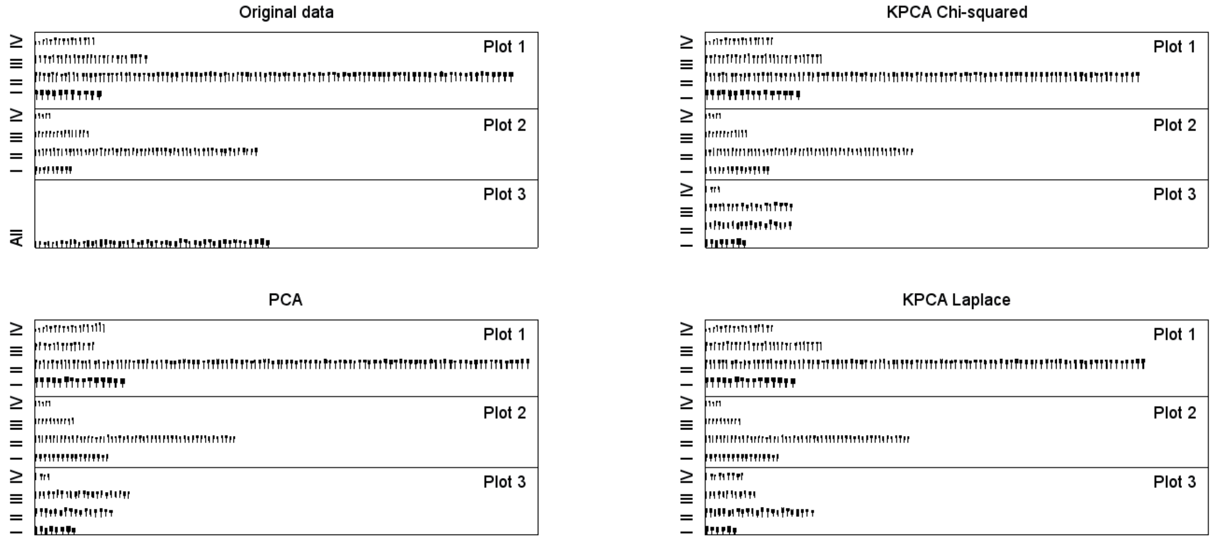


Figure 4. Probabilities of belonging to Kraft's classes (left panel) and probabilities of misclassifications (right panel)

The ordinate (y) axis presents values of probabilities, and the abscissa (x) axis shows crown classes.



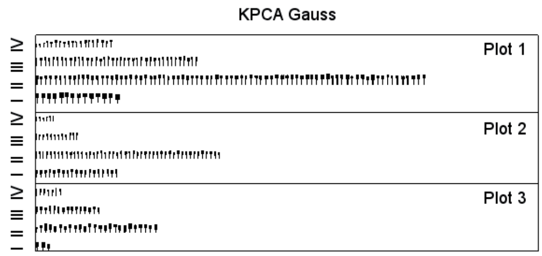


Figure 5. Visual assignment of tress into Kraft's classes

Matches present the DBH, H, CL, and CPA of trees. The handle of each match shows the diameter at breast height (DBH), the height of the entire match shows the height of the tree (H), the head presents the length of the crown (CL) and field crown projection area (CPA).

The model allows comparing the results of multivariate analysis with the original field-assigned method (Figure 5).

We performed the analysis using Scilab software (https://www.scilab.org/).

Results

Assignment of crown classes based on measured traits

The first plot

In the first plot, all four traits had a similar effect on the crown class distinction. The first two PCs in the PCA analysis explained 89% of the total variability (PC1 – 75%, PC2 – 14%) (Figure 1). The greatest contribution to PC1 had DBH (0.94) whilst on PC2 H and CL (–0.47 and 0.53, respectively) (Table 4). All the traits are directed to the side with the points representing the trees with the highest values, class I, the trees on the opposite side have the lowest values of given traits, class IV (similarly to further plots). The CPA and DBH allowed to distinguish clearly the I, IV, and partially III classes. The greatest impact on the separation of the II class had the variable of H.

In the KPCA method, PCs explained 89%, 53%, and 99% of total variability, when the Chi-squared, Laplace, and Gauss functions were used sequentially. The PC1 explained from 39 to 93% variability whilst PC2 from 6 to 14% (Figure 1). Consequently, it resulted in the visual separation of groups. The clearest visual division gave the KPCA Laplace. It allowed separating all classes linearly, although both PCs explained only 53% of the total variability.

The second plot

In the second plot, all four traits had also a similar effect on the distinction of crown classes. The PCA analysis explained 85% of the total variability (PC1 – 72%, PC2 – 13%) (Figure 2). The greatest contribution to PC1 had DBH (0.92) whilst on PC2 H and CPA (0.51 and –0.49, respectively) (Table 4). The variables of DBH and CL affected the clearest crown class separation. The variable of H had the greatest contribution to PC2 and the distinction of the IV class.

In the KPCA analysis, the Gauss and Chi-squared kernel functions explained best the total variability, i.e. 96% and 86%, respectively. Again, two PCs in the KPCA Laplace explained only 49% of the total variability. PC1 explained from 36 to 83% variability and PC2 from 13 to 14%. Results indicate that in this plot it was difficult to separate the I and II crown classes. Again, the best visual division gave the KPCA Laplace that additionally allowed to distinct the I class (Figure 2).

The third plot

In the third plot, the PCs in the PCA analysis explained 82% of the total variability (PC1 – 58%, PC2 – 24%) (Figure 3). Three traits (DBH, CL, CPA) had a similar effect on the crown class distinction. The greatest contribution to PC1 had DBH (0.87) and CPA (0.86) whilst on PC2 the greatest contribution had CL (–0.79) (Table 4).

The KPCA analysis showed similar results as in the previous plots. PCs explained 96% (Gauss) and 84% (Chi-squared) of the total variability, whilst only 42% when the Laplace function was used. PC1 explained from 27 to 91% variability and PC2 from 5 to 28% (Figure 3). Again, the clearest visual class separation gave the Laplace kernel function.

The comparison of crown class assignment

Results show that the best method of assigning the trees into biosocial classes is the KPCA Gauss (considering the percentage explanation of the total variability). Similar results gave also the KPCA Chi-squared and PCA analyses. However, the probabilities of misclassifications gave the lowest results both in the first (16%) and the second plot (25%) for the KPCA Laplace. For this function, the probabilities of belonging to crown classes were nearby to *a priori* probabilities. The empirical probabilities of trees belonging to Kraft's classes in the first and the second plot amounted to 0.07–0.11 in the I, 0.65–0.66 in the II, 0.17–0.18 in the III, and 0.06–0.10 in the IV classes (Figure 4, left side, *a priori*). These proportions were reflected best by the KPCA Laplace in the first plot, KPCA Chi-squared in the second, KPCA Laplace and Gauss in the third plots (Figure 4, left side). Moreover, in the third plot, the empirical probabilities of trees belonging to the I and IV Kraft's classes, for most of the functions, were like results obtained in the first and second plots. Unfortunately, the probabilities of belonging to the II and III classes differed substantially. They were lower by about 0.3 for the II, and higher by about 0.2 for the III classes.

The analysis of "matchstick" charts (Figure 5) allowed us to visually assign the trees into crown classes in all three plots. It indicated, similarly to the probabilities of belonging to Kraft's classes, that for the first two plots the KPCA Laplace and Chi-squared, as well as the PCA analysis only for the second plot, were visually consistent with the original crown class assessment. In the third plot, the closest results gave the KPCA Laplace and Gauss. The proportions of trees were consistent with the probabilities of belonging to crown classes for these kernel functions (Fig. 4).

Discussion

Our study presents a statistical use of measurable traits of trunk and crown to assess the crown classes of oak trees. It is worth mentioning that so far, a few studies have used similar statistical methods, e.g. Bechtold 2003, Zawieja and Kaźmierczak 2015, 2016. Such an attempt derives from practical difficulties in biosocial class assessment. They concern especially the subjectivity of the estimation procedure (Nigh and Love 2004). As it was mentioned in the introduction, assigning trees into a given class requires a lot of experience, and its accuracy depends on human judgments rather than on strict values. The above statement confirmed Kangas et al. (2004) during the research on the accuracy of visually assessed stand characteristics. A case study indicates a clear variation among technicians, especially in traits that include personal judgment. Furthermore, results showed that broadleaved classes were generally more difficult to estimate than coniferous. The accuracy of the field-assigned crown class depends also on its application. Although Kraft's classification was meant primarily only for even-aged stands, it is more often applied to uneven-aged stands. Thus, the research on the repeatability of crown position assessment in the Appalachian spruce-fir forest indicates that crown position is difficult to similarly reclassify on the second visit in uneven-aged stands (Nicholas et al. 1991). That is why many attempts have been done to suggest an alternative, a modified Kraft's classification.

Bechtold (2003) replaced a traditional crown class assessment with two alternative more repeatable traits – crown position and crown light exposure. An algorithm applied to the alternate variables estimated crown class with the same degree of accuracy as a field-assigned method. Moreover, the author pointed out that such traits supply more specific data about each tree than the crown class alone. Therefore, such an approach is potentially useful for modeling and other research studies. In our study, results indicated that the multivariate analysis, based on the directly measured traits, estimated crown classes of trees almost with the same results as a field-assigned method. All traits contributed to the crown class distinction. Thus, it indicates, similarly to the study conducted by Bechtold (2003), that such traits can be a potentially useful substitute for the traditional crown class assessment. Similar tree variables, i.e. DBH, H, relative DBH, H, CL, and crown depth together with the light model tRAYci were used by Nigh and Love (2004) to predict crown classes. The accuracy rates achieved 91% and 82% for the field-based and light-based assessments of crown classes, respectively. An additional useful statistical tool is the discriminant analysis that found application, i.e. to distinguish floristically different forest types (Thessler et al. 2008) and to assess the status of fire risk points (Jing et al. 2015). Such analysis was also used to allocate Scots pine trees into crown classes (Zawieja and Kaźmierczak 2015). The analysis indicated that four traits. i.e. height increment, DBH, slenderness, and tree basal area can be useful to divide trees into Kraft's classes. Also, the discriminant NKDA and LDA analyses were used to allocate trees into the biosocial classes. The three traits, i.e. DBH, H, and CPA, were selected for the model. The analysis showed a quite clear division (Kaźmierczak and Zawieja 2016, Zawieja and Kaźmierczak 2016). However, the discriminatory methods forced prior knowledge of the field-assigned crown class. Thus, in the present study, we applied the PCA and KPCA methods. It allowed us to assign the trees into the crown classes both in plots with and without *a priori* known biosocial position. In the first two plots, both PCs explained well the total variability by almost all used kernel functions. Moreover, we showed that for the KPCA Laplace and Chi-squared the probabilities of belonging to Kraft's classes were nearby to *a priori* probabilities. In other words, they were most consistent with the original field-assigned method. It was also confirmed by visual crown class distinction. The analysis of the "matchstick" chart (Figure 5) allowed us to visually assign the trees into Kraft's classes. The closest results, similarly, to empirical probabilities of trees belonging to Kraft's classes, were given by the KPCA Laplace and Gauss. It indicates that these kernel functions can be a potentially most useful statistical substitute for the crown class estimation.

The analysis showed that the greatest contribution to PC1, and thus the greatest contribution to the crown class distinction, had the DBH and crown parameters CL and CPA. A supplementary trait, with the greatest contribution to PC2, was the variable of H and CPA. Thus, it correlates with recent studies conducted by Bechtold (2003), Nigh and Love (2004), and Kaźmierczak and Zawieja (2016) that indicated a great role of alternative measurable traits in crown class assessment. The contribution of the listed traits to Kraft's class assessment derives from their joined interactions. As Turski et al. (2012) and Kaźmierczak (2017) stated, the crown length decreases along with the decrease of the biosocial position of the tree. Thus, the crown parameters CL and CPA are indicators of the 'growth energy'. Consequently, the crown plays a huge role in the life of the tree (Monserud 1975, Monserud and Sterba 1996). The size of the crown affects the annual ring increment, and thus affects the DBH and H traits (Daniels and Burkhart 1975, Jaworski et al. 1995). It indicates why such traits allowed us, though not perfect, to distinct separate crown classes.

Although the analysed traits allowed us to assign the trees into crown classes, the same variables were not always decisive in the division within all the plots. Moreover, the separation was not always clear. It was difficult to separate some crown classes using different kernel functions. The solution could be the creation of the neuron network. However, even if it was based on a higher number of trees and plots, it might still work incorrectly. The explanation lays in the lack of information about the direct position of trees in relation to their neighborhood, which is considered in the traditional field-assigned method. Perhaps supplementing the multivariate analysis with such a variable would allow gaining more precise and objective separation into crown classes. Moreover, a traditional crown class assessment is a more effective and faster way to determine the biosocial position of trees. In contrast to statistical analysis, it allows grouping trees in similar 'growth energy' groups, which is more appropriate, e.g. during thinning determination. Considering this limitation, we state that a traditional crown class assessment, despite its subjectivity, should continue to be of great importance in forestry practice. We also suggest that alternative traits of trunk and crown can be a potentially useful statistical substitute for crown class assessment. However, its application requires measurements that make it neither cheaper nor faster than a traditional field-assigned method.

Conclusion

In our study, we showed that chosen alternative traits of trunk and crown allowed, though not always perfect, to assign the trees into given crown classes. The greatest contribution to crown class distinction had the diameter at breast height and the parameters of crown, i.e. the length of the crown and the field crown projection area. Furthermore, results show that the best method of assigning the trees into biosocial classes is the KPCA Gauss (considering the percentage explanation of the total variability) and KPCA Laplace (considering the visual division). In the latter, the multivariate analysis resulted in a similar crown class distinction as the field-assigned method. However, its application requires measurements that make it neither cheaper nor faster than a traditional crown class assessment. It indicates that a traditional field-assigned method, despite its subjectivity, should continue to be of great importance in forestry practice. The alternative traits of trunk and crown used in the multivariate analysis can be a potentially useful statistical substitute for crown class assessment.

Author contributions

BZ, KT, and KK – Conceptualization, Methodology, Formal analysis, Reviewing, and Editing. KT – Writing – Original Draft. KK and TN – Investigations.

Acknowledgments

We thank the authorities of Piaski Forest District and Zielonka Experimental Forest District for allowing us to conduct our research.

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