Citation*

Aertsen W., Kint V., Van Orshoven J., Muys B. 2011. Evaluation of modelling techniques for forest site productivity prediction in contrasting ecoregions using stochastic multicriteria acceptability analysis (SMAA). *Environmental Modelling & Software*, 26(7), 929-937.

DOI: [10.1016/j.envsoft.2011.01.003](https://doi.org/10.1016/j.envsoft.2011.01.003)

Authors: Wim AERTSEN^a, Vincent KINT^a, Jos VAN ORSHOVEN^a, Bart MUYS^{a*}

^a Division Forest, Nature and Landscape, Katholieke Universiteit
Leuven, Celestijnenlaan 200E-2411, BE-3001 Leuven, Belgium;

* Corresponding author Bart Muys, Tel. +3216329721, Fax
+3216329760, E-mail bart.muys@ees.kuleuven.be

*Elsevier authorized the authors to post this revised personal version of the text of the final journal article on the author's institutional server, incorporating the complete citation and with a link to the Digital Object Identifier (DOI) of the article.

Creative Commons Attribution-Noncommercial-Share Alike 2.0 Belgium License

Permissions beyond the scope of this license may be available at

<http://www.elsevier.com/wps/find/authorsview.authors/copyright#whatrights>

14 **Title page**

15 **a. TITLE:** Evaluation of modelling techniques for forest site productivity prediction in
16 contrasting ecoregions using Stochastic Multicriteria Acceptability Analysis (SMAA)

17 **b. AUTHORS:** Wim AERTSEN^a, Vincent KINT^a, Jos VAN ORSHOVEN^a, Bart MUYS^a

18 **c. AFFILIATIONS:** Department of Earth and Environmental Sciences, Katholieke
19 Universiteit Leuven, Celestijnenlaan 200E Box 2411, BE-3001 Leuven, Belgium;

20 **d. CORRESPONDING AUTHOR:** Bart Muys, Tel. +3216329721, Fax +3216329760,
21 E-mail bart.muys@ees.kuleuven.be

22 **e. PRESENT ADDRESSES:** same

23 **f. ADDRESS FOR PROOFS:** Bart Muys, Division Forest, Nature and Landscape,
24 K.U.Leuven, Celestijnenlaan 200E Box 2411, BE-3001 Leuven, Belgium.

Abstract

Accurate estimation of site productivity is crucial for sustainable forest resource management. In recent years, a variety of modelling approaches have been developed and applied to predict site index from a wide range of environmental variables, with varying success. The selection, application and comparison of suitable modelling techniques remains therefore a meticulous task, subject to ongoing research and debate.

In this study, the performance of five modelling techniques was compared for the prediction of forest site index in two contrasting ecoregions: the temperate lowland of Flanders, Belgium, and the Mediterranean mountains in SW Turkey. The modelling techniques include statistical (multiple linear regression - MLR, classification and regression trees - CART, generalized additive models - GAM), as well as machine-learning (artificial neural networks - ANN) and hybrid techniques (boosted regression trees - BRT). Although the selected predictor variables differed largely, with mainly topographic predictor variables in the mountain area versus soil and humus variables in the lowland area, the techniques performed comparatively similar in both ecoregions.

Stochastic Multicriteria Acceptability Analysis (SMAA) was found a well-suited multi-criteria evaluation method to evaluate the performance of the modelling techniques. It has been applied on the individual species models of Flanders, as well as a species-independent evaluation, combining all developed models from the two contrasting ecoregions. We came to the conclusion that non-parametric models are better suited for predicting site index than traditional MLR. GAM and BRT are the preferred alternatives for a wide range of weight preferences. CART is preferred when very high weight is given to user-friendliness, whereas ANN is recommended when most weight is given to pure predictive performance.

48 **Keywords:** Mediterranean mountain forest, temperate lowland forest, predictive modelling,
49 boosted regression trees, artificial neural networks, generalized additive models, site index

1. Introduction

The assessment of site productivity is fundamental to sustainable forest resource management. One of the most widely used indicators of forest site productivity is the site index, i.e. the mean height of the dominant trees growing on a site at a reference age (Szwaluk and Strong, 2003). Site index can be estimated both directly and indirectly. For homogeneous even-aged stands, site index can be estimated directly from the mean height of the dominant trees and the age of the stand. But in mixed or uneven-aged stands, or in the case of stand conversion to other tree species, of afforestation of non-forested land, or under changing site conditions over time, direct estimation is not possible (McKenney and Pedlar, 2003). For such cases site index can be estimated indirectly by assessing relationships between site index and environmental variables (Corona et al., 1998; Curt et al., 2001), landscape characteristics (Iverson et al., 1997) and/or understorey vegetation characteristics (Bergès et al., 2006).

In recent years, a variety of modelling approaches has been developed and applied to predict site index from a wide range of environmental variables, with varying success (see e.g., Corona et al., 1998; Chen et al., 2002; Bergès et al., 2005). Moreover, most models were developed based on limited data sets, narrowing their application to only one species or a small geographic extent. The development of more advanced non-parametric and machine learning techniques and the growing availability of geodatasets at high spatial resolution are opening new opportunities to predict forest site quality with greater accuracy and with a wider application range (McKenney and Pedlar, 2003; Wang et al., 2005).

Unlike for the prediction of species distributions, for which specific niche modelling software tools have been developed incorporating different modelling techniques (Thuiller et al., 2009), no ready-to-use software is available for the prediction of continuous variables, such as

73 site index. Hence, the selection, application and comparison of suitable techniques remains a
74 meticulous task, subject to ongoing research and debate. In a previous study we compared
75 five modelling techniques for the prediction of site index of three tree species in the Taurus
76 mountains of Turkey (Aertsens et al., 2010). Statistical (multiple linear regression - MLR,
77 classification and regression trees - CART, generalized additive models - GAM), as well as
78 machine-learning (artificial neural networks - ANN) and hybrid techniques (boosted
79 regression trees - BRT) were tested and ranked based on a multi-criteria decision analysis
80 (MCDA). GAM came out as the preferred technique for the considered species and region.
81 However, the generalizability of these results to species and environmental conditions outside
82 the Mediterranean mountain region remained an open question. Therefore a similar research
83 setup was established in temperate lowland forests in Flanders, Belgium. In contrast with the
84 Taurus mountains, the site index in the plains of Flanders is not expected to be driven by
85 topographic and climatic gradients, but rather by soil variables determining nutrient and water
86 availability. The sampling strategy was therefore established mainly along these gradients
87 (Bergès et al., 2005). To check whether the same modelling techniques would perform
88 similarly on other tree species in a contrasting ecoregion, they have been applied in the same
89 way as on the Turkish data.

90 MCDA has been proven an important tool to support decision makers in many domains of
91 environmental planning and management (*e.g.* Castelletti et al., 2010; Chen et al., 2010),
92 combining the information from several criteria to form a single index of evaluation. In the
93 earlier study (Aertsens et al., 2010), an MCDA using different performance criteria under
94 different scenarios was adopted as an objective way to rank the different techniques.
95 Nevertheless, the attribution of weights for describing the relative importance of different
96 criteria remained a more or less subjective matter, driven by the authors' experiences and
97 preferences. Several weight elicitation methods have been suggested in order to find the true

preferences of a decision maker. However, the suggested procedures tend to result in different weights for the same problem. Reaching consensus about exact weights can be difficult (Lahdelma and Salminen, 2001; Kangas and Kangas, 2003). Stochastic Multicriteria Acceptability Analysis (SMAA) has been proposed as an alternative for traditional MCDA. SMAA is a family of MCDA methods developed for situations where criteria values and/or weights are uncertain or inaccurate (Lahdelma et al., 1998). Moreover, it makes efficient use of mixed ordinal and continuous data. SMAA methods explore the weight space in order to describe the valuations that would make each alternative the preferred one, or that would give a certain rank to an alternative, instead of resulting in a ranking (Lahdelma and Salminen, 2001; Kangas et al., 2003; Kangas and Kangas, 2003, 2005; Tervonen and Figueira, 2008). Many studies comparing ecological modelling techniques conclude that in general no best technique exists, but all depends on the goals of the study (Guisan and Zimmermann, 2000; Segurado and Araújo, 2004; Jakeman et al., 2006). SMAA provides a good basis for evaluating alternatives, dependent on the preferences and goals of the end-user.

The aim of this study is to evaluate site index modelling techniques by applying SMAA to an extensive dataset from two contrasting regions covering each three tree species with very different ecological traits. Results from an oromediterranean region in Turkey for Calabrian pine (*Pinus brutia* Ten.), Crimean pine (*Pinus nigra* Arnold ssp. *pallasiana* (Lamb.) Holmboe) and Lebanon cedar (*Cedrus libani* A. Rich), published earlier (Aertsens et al., 2010), are complemented here with new results from the temperate lowland region of Flanders for pedunculate oak (*Quercus robur* L.), common beech (*Fagus sylvatica* L.) and Scots pine (*Pinus sylvestris* L.). The specific objectives of this study are:

- (1) to compare the modelling techniques with respect to their predictive performance for site index of pedunculate oak, common beech and Scots pine in Flanders, Belgium;

- (2) to analyse the acceptability of the techniques for use in Flanders with SMAA;
- (3) to compare the acceptability and behaviour of the techniques when applied on two contrasting ecoregions: the temperate lowland of Flanders and the Mediterranean Taurus mountains in Turkey;
- (4) to formulate final recommendations in choosing an appropriate technique for modelling site index.

2. Material and methods

2.1 Study area and data collection

The study area covers the Region of Flanders, Northern Belgium (50°40' - 51°31' N, 2°32' - 5°55' E - Fig. 1), a lowland area of 13521 km² without strong topographic or climatic gradients. The climate is oceanic (mean annual temperature 9.75-10.5°C; annual precipitation 733-832mm). The main geological variability is due to aeolian deposits with pronounced North-South gradient of increasing silt fraction, and local shallow tertiary substrates (clay/sand).

186 research plots were selected (76 plots of oak, 55 of beech and 55 of pine) spread throughout the territory of Flanders: (Fig. 1). To do so, the database of inventory plots in public forests 'Bosdat' (Flemish Agency for Nature and Forest) was queried for near-homogeneous, even-aged, normally stocked high-forests of the target species of at least 50 years old using a two-step approach: The first step consisted of a stratified random selection of stands of the tree species, evenly distributed over five productivity classes, based on a-priori determination of the site index from height measurement and age estimation. Since site index is mainly determined by site quality (Assmann, 1970), this selection is assumed to cover a substantial part of the regional site variability of actual oak, beech and pine stands in

145 Flanders. In the second step additional plots were selected to fill gaps in common forest soil
146 types and in geographical coverage.

147 Data collection was carried out between October 2007 and February 2009. A research plot
148 (about 1000 m²) consisted of (1) two concentric circular zones with radius 9m and 18m and
149 (2) a 16-point regular grid (10 m spacing) in a square of 30 m by side.

150 The response variable considered is site index. Site index is defined as the dominant height of
151 a homogeneous even-aged stand at the reference age of 100 years. From the tree height
152 measurements in each research plot, dominant height was calculated as the mean height of the
153 five thickest trees. Tree age was estimated from ring counts and adjusted by extrapolating for
154 missing rings (due to off-pith coring and to account for rings formed before the 1 m coring
155 height was reached). Based on the dominant height and the age of the stand, site index was
156 calculated from species dependent dominant height growth models (Jansen et al., 1996).

157 Site quality was assessed by humus quality description, physicochemical analysis of the
158 mineral topsoil, vegetation survey, soil compaction measurement and compilation of available
159 site information. The set of variables is summarized in Table 1.

160 Humus form, depth of the organic accumulation in the mineral topsoil (0-30cm), and soil
161 depth were determined in the 16-point grid, and then averaged. Humus form was determined
162 on the scale of Jabiol et al. (2007) and converted to the index of Ponge (2002) with values
163 ranging from 1 (eumull) to 9 (mor). Soil depth was defined as the depth of the 3 MPa
164 compaction limit measured with a penetrometer, assuming that this is the maximal resistance
165 tree roots can overcome. The thickness of the humus layer was determined at one
166 representative grid point.

A bulked topsoil sample (0-30cm, 16 sample points mixed) has been analysed for soil texture fractions (laser diffraction), pH-CaCl₂, carbon content (LOI), nitrogen content (Kjeldahl), plant available phosphor content (Bray & Kurtz) and C:N ratio. Variables derived using best available pedotransfer functions include bulk density (De Vos et al., 2005), available water capacity (AWC), air capacity (AC) and permanent wilting point (PWP) (Teepe et al., 2003).

A vegetation survey was carried out during spring and summer on a 10x10 plot around each sample tree. Based on species abundance in the vegetation and shrub layers, Hill-values for moisture (mF), light (mL), reaction (mR) and nitrogen (mN) were calculated (Hill et al., 1999), as well as the combined mN*mR index of soil trophicity (Muys and Granval, 1997) and the Shannon diversity index.

Additional site quality variables were derived from available geodatasets for the region. These include the soil map of Belgium (drainage class), a high-resolution DEM (altitude, slope, curvature, transformed aspect $TRASP = [1 - \cos((\pi/180)(\theta-30))]/2$; with θ the slope azimuth measured from the true north) and N-deposition (Bleeker and Van Deursen, 2007).

Finally, climate variables only included the number of frost days (below -4 °C). Initial analyses also included averages for total precipitation and mean temperature (annual, spring, summer, growing season), but due to low variability and high correlation with other environmental variables, these variables were omitted to reduce the risk of confounding factors. For each sample tree, variables were compiled using data from the three most nearby weather stations in Belgium (KMI) or across the border with The Netherlands (KNMI) for the period 1951-2008.

2.2 Modelling techniques and performance

One of the objectives of the research was to compare the performance of five modelling techniques for forest site index in Flanders with their performance in the Taurus Mountains in Turkey which was reported in a previous study (Aertsen et al., 2010). To this end it was important to apply the same techniques. One parametric technique (MLR), two statistical non-parametric techniques (GAM, CART), one machine learning technique (ANN) and one hybrid technique (BRT) were applied as described in Aertsen et al. (2010). Model fit and predictive performance after cross-validation were quantified by the coefficient of determination (R^2), coefficient of efficiency (CE), the (relative) root mean squared error ((r)RMSE), Akaike information criteria (AIC), Bayesian information criteria (BIC) and adjusted R^2 (R^2_{adj}), according to Aertsen et al. (2010).

2.3 Stochastic Multicriteria Acceptability Analysis (SMAA)

In contrast with most traditional MCDA methods, the main purpose of SMAA is not to determine the recommended alternative (i.e. modelling technique) given a set of criteria and weights, but to determine which weight values would typically support the various alternatives for being selected (Kangas and Kangas, 2005). There are several versions of SMAA. SMAA-2 extends the original SMAA by considering all ranks in the analysis. This helps to identify good compromise alternatives in case the acceptability is distributed among extreme alternatives, each of which obtains high ranks according to a limited set of weights, but low ranks through other weights (Lahdelma and Salminen, 2001). SMAA-O in turn enables the handling of ordinal information. The ordinal criteria values are replaced by random quantitative values which are simulated numerically using Monte Carlo iterations in a way that preserves the ordinal rank information (Tervonen and Lahdelma, 2007). In this study SMAA has been applied using the JSMAA software, version 0.6.2 (Tervonen, 2010), combining SMAA-2 and SMAA-O and assuming a linear preference model.

The fundamental idea of SMAA is to provide decision support through four descriptive measures calculated as multidimensional integrals over stochastic parameter spaces (Lahdelma et al., 1998; Tervonen and Figueira, 2008). (1) The *rank acceptability indices* [0-1] depict the probabilities of placing an alternative at a certain rank while taking all the input data into consideration. (2) The *holistic acceptability index* [0-1] measures the “overall acceptability” of the alternatives, based on the weighted sum (using centroid meta-weights) of the probabilities for different ranks (Lahdelma and Salminen, 2001). The holistic acceptability indices have an important practical use: sorting the alternatives by their holistic acceptability index brings similar alternatives close to each other and makes the rank acceptability index table much more descriptive (Kangas et al., 2006). (3) The *central weight vector* of each alternative is defined as the expected centre of gravity of the favourable weight space. This represents the preferences of a hypothetical decision maker supporting this alternative as the preferred one. Presenting the central weights of different alternatives to decision makers may help them to understand how different weights correspond to different choices with the assumed preference model. (4) The *confidence factor* [0-1] finally indicates the probability for an alternative to be the preferred one with the preferences expressed by its central weight vector (Tervonen and Figueira, 2008).

2.4 Evaluation criteria

The criteria used for the evaluation of alternative modelling techniques using SMAA were mainly identical to the ones used in our earlier site index study (Aertsen et al. 2010). Three uncorrelated predictive performance measures (RMSE, AIC and R^2 adj), calculated on the model predictions after 10-fold cross-validation, were used as quantitative evaluation criteria, with highest preference for RMSE and AIC closest to zero, whereas for R^2 adj closest to unity. Considering that model accuracy is only one of the evaluation criteria important in real-life

applications (Jakeman et al., 2006), also two qualitative criteria i.e. ‘ecological interpretability’ and ‘user-friendliness’ were selected. ‘Ecological interpretability’ is referring to the degree in which the model incorporates the relative importance of predictor variables and how site index is changing with changes in predictor variable(s). This is particularly important for understanding and checking the ecological soundness of the model. ‘User-friendliness’ is referring to the simplicity of the technique, the statistical and technical background necessary to apply the technique and the simplicity to upscale the results to full-coverage site index maps. The latter criteria were scored on an ordinal scale (Table 2) based on the authors experiences, described in Aertsen et al. (2010). Given the fact that SMAA only describes the weight space and leaves the attribution of weights to the end-user, the criteria space could be extended with R^2 of the calibration data as an additional evaluation criterion, not used in our earlier study. A goodness-of-fit indicator as R^2 can be a good complement on the predictive performance measures and can provide important information for end-users more interested in describing the relationships present in the data, rather than developing good predictive models.

First, SMAA was applied separately on the models developed for each tree species in Flanders. Stochasticity in the output was generated by the conversion of ordinal criterion values into quantitative values during the Monte Carlo iteration process, whereas the quantitative evaluation measures of the different models were used as exact criterion values. In a second step SMAA was applied as a species-independent evaluation of the performance of different techniques for modelling site index. To do so, mean criterion values and standard deviations were calculated for each technique based on the values for the six modelled species in the two contrasting ecoregions. These values were implemented in the SMAA assuming a Gaussian distribution. The variability of these criterion values introduced an additional source of stochasticity in the analysis.

3. Results

3.1 Site index models for Flanders

A total of 15 site index models were built, using 5 modelling techniques for each of the 3 species. All models were critically investigated for confounding factors and collinearity between explanatory variables and all basic assumptions were checked. Investigation of the predictor variables entering the different models confirmed the importance of soil variables as site quality factors for this region (Table 3). Soil texture fractions are present in all the models mostly accompanied by the soil C:N ratio for oak models and the soil pH for beech models. Only one of the developed models is lacking any soil predictor: the CART model for pine. But the performance measures (Table 4) indicate unmistakably that the latter is the worst predictive model developed in this study, with even a negative coefficient of efficiency (CE) on the validation data, indicating a prediction worse than simply using the mean value of all observations. In addition to the soil variables, also the humus variables are important site index predictors in this region. Especially the thickness of the ectorganic horizon (humus thickness) and the thickness of the humus-rich mineral horizon (Ah thickness) appear in most developed models. Apparently topographic variables are of minor importance in Flanders, which is not surprising considering the little topographic variation in the region (Table 1).

The measures of performance are summarized for each model in Table 4. Better model performance is realized with lowest (R)RMSE, AIC and BIC values and with R^2 , adjusted R^2 and CE closest to unity. A distinction has been made between the values for model calibration and values for 10-fold cross-validation, while for the evaluation of the performance only the predictive performance, i.e. the validation values, is taken into account. By comparing the predictive performance of all models, similar trends can be observed for all species. The best performance based on RMSE, R^2 and CE, is obtained by the ANN-models, followed by the

GAM and BRT-models respectively. MLR and especially CART are scoring worse for these indicators. When traditional measures are adjusted for the number of free parameters involved in the model, which is the case for AIC, BIC and adjusted R^2 , the performance of ANN becomes worse. Techniques such as GAM and BRT are still scoring well for these indicators. The less complex models like MLR and CART score also relatively better when model performance is penalised for the complexity of the model. Similar trends have been observed in the site index modelling study in Turkey (Aertsen et al., 2010) where also the non-parametric techniques, except for CART, outperformed MLR for predicting site index. ANN performed the best for R^2 and RMSE, but when complexity was taken into account, it was penalized for its complex models. GAM models were performing slightly better than BRT models and obtained the overall best performance. In contrast with the models in Flanders, topographic variables such as elevation, slope and landscape position were important predictor variables for site index in this mountain area in combination with soil variables as organic matter content, soil depth and soil pH.

3.2 SMAA for Flanders

To check whether the outcomes of the techniques are consistent for different species, deterministic SMAA has been performed on the three modelled species separately, with a selection of the calculated performance indices (Table 4) as exact criterion values and the qualitative evaluation measures on an ordinal scale (Table 2). With exact cardinal criterion values stochasticity is low and only introduced by the conversion of ordinal to continuous values, resulting in high confidence factors for the central weight vectors, with some exceptions for MLR and CART though (Table 5). BRT and GAM obtain consistently high holistic acceptability index values and also high rank acceptability index values for the first two ranks (Table 5), only slightly exceeded by ANN for pedunculate oak. The central weight

vectors for BRT and GAM are for all species those with the most even criteria weights distribution (Fig. 2). The high confidence factors and the central weight vectors of both techniques indicate that they are preferred over all other techniques when weights of all criteria are almost evenly distributed. Comparison of the central weight vectors shows that GAM will be preferred when a little more weight is given to RMSE, R^2 adjusted and ecological interpretability, while BRT is preferred with higher weights for user-friendliness. For AIC and R^2 the tendency is not consistent between species. The very low scores of MLR and CART for the first two rank acceptability indices in combination with the low confidence factors give indication that these two techniques are very unlikely to become the most preferred one by any decision maker. For pedunculate oak MLR has even no central weight vector (Fig 2A) meaning that it will under no circumstances become the preferred one. Although ANN also scores badly for the first two rank acceptability indices for beech and pine, its confidence factor of 1 indicates that with suitable preferences, i.e. high preferences for R^2 and RMSE (Fig. 2B and 2C), this alternative is nevertheless the preferred one for these species. Moreover for oak, ANN scores very high with the highest holistic and first rank acceptability indices, indicating that in this case ANN will be the preferred alternative for a wide range of criteria weights.

3.3 Species-independent SMAA for two contrasting ecoregions

To draw general conclusions about the suitability of techniques for modelling site index with different preferences, individual test cases are not satisfactory. To this end a species-independent analysis has been carried out. In the present and our previous site index modelling study in Turkey (Aertsen et al., 2010), the site index of six tree species in one of two contrasting ecoregions has been modelled with five different techniques. The same performance indices have been calculated for all models, resulting for each combination of

technique and performance index in a mean value with standard deviation (Table 6). SMAA has been applied based on the same criteria as before, with the mean performance index as criterion value and uncertainty represented by its standard deviation. This uncertainty results in lower confidence factors (Table 5), making it more difficult to develop strong conclusions. Based on the holistic, first and second rank acceptability indices, GAM seems for most of the criteria/weight combinations the preferred technique for modelling site index (Table 5). The relatively high confidence factor indicates that for its central weight vector (Fig 2D), with almost equal weights for all involved criteria, GAM has a high possibility to be preferred. BRT has a slightly lower holistic and first rank acceptability index, with a very similar central weight vector (Fig. 2D), indicating that this technique will be for most weight combinations a good alternative for GAM. ANN and CART end up with lower holistic, first and second rank acceptability indices, but their central weights clearly differ from those of both GAM and BRT (Fig. 2D). Choosing CART would for example require a weight of about 40% for user-friendliness, while in order to choose for ANN almost half of the weight should be equally divided over R^2 and RMSE. Despite the low holistic acceptability indices, these alternatives could be preferred if the decision makers reach consensus about such preferences. The low holistic, first and second rank acceptability indices in combination with the low confidence factor will make MLR rarely come up as the preferred technique.

4. Discussion

4.1 Predictive performance

Based on the predictive performance, non-parametric techniques as BRT, GAM and ANN are better suited for modelling site index than the traditional MLR for all modelled species. Only CART performed worse for modelling site index of beech and pine. Despite CART's poor predictive performance, as earlier observed and discussed (Moisen and Frescino, 2002;

Aertsen et al. 2010), the technique is well suited for discovering relationships in the dataset, as shown by the relatively high R^2 at calibration in contrast to the low R^2 at validation. These characteristics have led to the development of a technique as BRT, combining the CART with a boosting algorithm to improve its predictive performance (Elith et al., 2008). In this sense it is not surprising that BRT outperforms CART for predicting site index. The suitability for exploring ecological relations is maintained in the BRT technique and this is confirmed in this study. Its high model performance at calibration with a relatively lower performance at validation, compared to GAM, shows an inclination towards overfitting. While overfitting in predictive modelling is often seen as a problem, the flexibility in the modelling of BRT enables an accurate description of the relationships in the data, provided that the overfitting is appropriately controlled (Elith et al., 2008). BRT's capability to model interactions among predictor variables did not result in an improved predictive performance over GAM as observed earlier by Leathwick et al. (2006) and Moisen et al. (2006). On the other hand the ability of ANN to model complex relations did result in a better performance based on the traditional performance indices (R^2 , CE, RMSE). However a lower performance was observed when the number of free parameters has been taken into account (AIC, BIC, R^2 adj).

As can be expected, site quality in the lowlands of Flanders is explained by other environmental variables than in the Mediterranean mountains of Turkey. Whereas in the Turkish region the largest amount of variance in site index was explained by topographic variables, often correlated with climatic variables, site quality in Flanders was mainly explained by means of soil and humus related variables. Similar observations as ours for Flanders have been recorded by Bergès et al. (2005) for sessile oak in nearby northern France. Initially we expected a low predictive performance due to the absence of strong topographic and climatic variation in Flanders. However, the textural gradient (with an increasing silt fraction from north to south) in combination with a good sampling design and highly accurate

field measurements made it possible to explain a similar amount of variance in Flanders as in a region with pronounced topography, as the Taurus mountains. The achievement of a complete sampling design stratified according to the main ecological gradients is indeed crucial for good site index modelling (Bergès et al., 2005).

4.2 Stochastic Multicriteria Acceptability Analysis

SMAA applied separately on the three species in Flanders confirms the outperforming of MLR and CART by the other techniques. Even with inclusion of the qualitative evaluation measures, where both CART and MLR score the highest for user-friendliness, they have an extremely low first rank and holistic acceptability index (Table 5). Moreover, the low confidence factors for beech and pine suggest that even with a weight distribution according to their central weight vector, there is little chance that one of these techniques will be preferred over the others. The SMAA results are very similar for beech and pine, while the oak case is slightly different (Table 5 and Fig. 2). For oak MLR has even no central weight vector at all, meaning that it will in no case end up as the preferred technique based on these data and criteria. The central weight vectors of ANN and CART are also more similar to those of BRT and GAM for the oak modelling than for the two other species. These findings can be related to the conclusion of Elith et al. (2006) who compared techniques for species distribution modelling in different regions. In regions where overall performance was high, the ‘‘best’’ methods performed well, although most methods were able to produce models of reasonable quality for many of the species. Exceptions to the usual ranking of methods sometimes appeared in regions in which overall predictive performance was poor, with no clear consistent cause. In these regions the good methods still showed moderate success. In our study the overall predictive performance of oak is also noticeably lower than for the two other species, resulting in a highest holistic and first rank acceptability index for ANN with

407 still moderate success for BRT and GAM, while for the other two species with an overall
408 higher predictive performance ANN scores much lower than BRT and GAM. Based on this
409 we conclude that BRT and GAM are the best techniques when there are clear relations
410 between the response and predictor variables and a large amount of variance can be explained.

411 The general trends of the performance of the different modelling techniques were highly
412 comparable in the Flemish study compared to the Turkish study and also the experiences of
413 the authors in building and interpreting the models remained more or less identical. Therefore
414 it is not surprising that the SMAA for Flanders leads to similar conclusions as the
415 conventional MCDA did for Turkey. Nevertheless, the results with SMAA allow for broader
416 interpretation and are less driven by the authors' preferences, leading to more reliable
417 conclusions. In traditional MCDA criteria weights are predefined, so that the selection of the
418 criteria is very important. This is probably less the case in SMAA where end-users can
419 explore the weight space according to their own preferences and in that way still eliminate
420 unimportant criteria, by giving it little or no weight. The focus of the Turkish study was
421 mainly on predictive modelling of site index, whereas SMAA allowed introducing R^2 on the
422 calibration data as an additional criterion, giving end-users the opportunity to rate also the
423 ability to describe ecological relationships in the data. Decision makers are also not forced
424 into defining criteria weights, as all weight combinations are left open for end-users. Based on
425 the Turkish study, with weights defined for two scenarios, ANN and CART were not suited
426 for modelling site index. In contrast, SMAA in this study shows that the central weight vector
427 of both techniques for all species clearly differs from the one of GAM and BRT. This
428 indicates that in specific situations, with high weights for specific criteria, these techniques
429 can still be preferred, all depending on the preferences of the end-users.

The ability to incorporate uncertainty in the criterion values is another advantage of SMAA over most traditional MCDA techniques. Mean criterion values and standard deviations have been calculated for the site index models of the six tree species in one of two contrasting ecoregions. In this way the results of six different cases could be combined to assess general recommendations for modelling site index. Although MLR is the most widely used technique for modelling site index, SMAA reveals that the technique will very rarely come up as the best available technique, irrespective of the preferences of end-users. This confirms the higher suitability of most non-parametric techniques over conventional parametric techniques to fit the non-linear relationships between response variable and environment (Guisan et al., 2002; Leathwick et al., 2006). GAM and BRT end up with the highest holistic, first and second rank acceptability indices, meaning that those techniques will be preferred in a wide range of criteria weight distributions. The similarity of their central weight vectors indicates that both techniques are good alternatives for each other. The different preferences for ecological interpretability and user-friendliness, lead to a central weight vector of BRT with little higher weight for user-friendliness, and little lower weight for ecological interpretability. For the quantitative criteria central weight distributions are very similar and almost equally distributed (Fig. 2D). GAM and BRT are clearly good alternatives in a wide range of weight distributions, while ANN and CART will only become preferred techniques for a specific set of weights.

Statistical models in ecology may be explanatory or predictive. Explanatory models seek to provide insights into the ecological processes that produce patterns, while predictive models typically seek to provide the user with a statistical relationship between the response and a series or predictor variables (Guisan et al., 2002), which can be applied outside the training set. GAM and BRT seem to be the most suited techniques in balancing both contrasting types. Their partial dependence plots and relative contributions of predictor variables can provide

good insights in the factors causing variation in site index, leading to good explanatory models. On the other hand they also provide a strong statistical relationship between the response and a series of predictor variables for use in predicting site index at new, previously unsampled locations. Moreover these techniques include variable reduction in the analytical phase and aims at a model that predicts the ecological attribute(s) of interest from a restricted number of predictors (Guisan et al., 2002). ANN on the other hand is more an example of a purely predictive modelling technique (black-box), simply searching for the best connections between response variable and the suite of predictor variables, without providing information on the shape of these relationships or the importance of the predictor variables. While the predictive success can be very high, it does not mean automatically that the shape of a response curve for an environmental predictor is ecologically rational, giving little guarantee to apply the model in other regions (Austin, 2007).

Although the results of the different techniques were to a large extent similar for the six modelled species in the two contrasting ecoregions, there is no guarantee that this will be the case in other situations. The low confidence factors of the species-independent SMAA compared to the SMAA of the individual species confirm that our findings are not unambiguous. As all kind of relationships can be present in datasets, some techniques will be better suited than others to reveal them. So the best way to analyse or predict site index is still applying different techniques and comparing their outcomes. On the other hand, in case there is no possibility of applying different techniques, the consistency of our results for different species in contrasting ecoregions and the outcome of the SMAA provide a good base for choosing the appropriate technique for modelling site index from environmental variables, depending on the end-users preferences.

5. Conclusions

The performance of five modelling techniques has been compared for the prediction of forest site index in two contrasting ecoregions: the temperate lowland of Flanders and the Mediterranean Taurus mountains in Turkey. Although the selected predictor variables differed largely, with mainly topographic predictor variables in the mountain area versus soil and humus variables in the lowland area, the techniques performed comparatively similar in both ecoregions. Stochastic Multicriteria Acceptability Analysis (SMAA) was successfully applied to formulate final recommendations for choosing appropriate techniques for modelling site index depending on the goal of the study. Non-parametric techniques are better suited for modelling site index than traditional MLR. GAM and BRT are the preferred alternative for a wide range of weight preferences, while CART and ANN become the preferred techniques in more specific situations; CART when very high weight is given to user-friendliness, while ANN when most weight is given to pure predictive performance.

Acknowledgements

This research was supported by the Research Fund K.U.Leuven (OT/07/046) and the SimForTree project (www.SimForTree.be; IWT-SBO contract 060032). Special thanks go to Marc De Vrieze and Joost Malliet for the tremendous amount of field work they accomplished as part of this research, the Agency for Nature and Forest for granting access permission to the forests and for providing valuable forest inventory data and Ward Delabastita for introducing SMAA in our research group.

References

Aertsen, W., Kint, V., Van Orshoven, J., Özkan, K., Muys, B., 2010. Comparison and ranking of different modelling techniques for prediction of site index in Mediterranean mountain forests. *Ecol. Model.* 221, 1119–1130.

502 Assmann, E., 1970. The principles of forest yield study. Pergamon Press, Oxford.

503 Austin, M., 2007. Species distribution models and ecological theory: a critical assessment and
504 some possible new approaches. Ecol. Model. 200, 1-19.

505 Bergès, L., Chevalier, R., Dumas, Y., Franc, A., Gilbert, J.M., 2005. Sessile oak (*Quercus*
506 *petraea* Liebl.) site index variations in relation to climate, topography and soil in even-aged
507 high-forest stands in northern France. Ann. Forest Sci. 62, 391-402.

508 Bergès, L., Gegout, J.C., Franc, A., 2006. Can understory vegetation accurately predict site
509 index? A comparative study using floristic and abiotic indices in Sessile oak (*Quercus*
510 *petraea* Liebl.) stands in northern France. Ann. Forest Sci. 63, 31-42.

511 Bleeker, A., Van Deursen, W., 2007. Modelling the nitrogen deposition to afforested systems,
512 in: Heil, G., Muys, B., Hansen, K., Environmental effects of afforestation in North-Western
513 Europe. Springer, Dordrecht, pp. 109-128.

514 Castelletti, A., Lotov, A.V., Soncini-Sessa, R., 2010. Visualization-based multi-objective
515 improvement of environmental decision-making using linearization of response surfaces.
516 Environ. Model. Softw. 25, 1552-1564.

517 Chen, H.Y.H., Krestov, P.V., Klinka, K., 2002. Trembling aspen site index in relation to
518 environmental measures of site quality at two spatial scales. Can. J. Forest Res. 32, 112-119.

519 Chen, Y., Yu, J., Khan, S., 2010. Spatial sensitivity analysis of multi-criteria weights in GIS-
520 based land suitability evaluation. Environ. Model. Softw. 25 1582-1591.

521 Corona, P., Scotti, R., Tarchiani, N., 1998. Relationship between environmental factors and
522 site index in Douglas-fir plantations in central Italy. Forest Ecol. Manage. 110, 195-207.

523 Curt, T., Bouchaud, M., Agrech, G., 2001. Predicting site index of Douglas-fir plantations
524 from ecological variables in the Massif Central area of France. *Forest Ecol. Manage.* 149, 61-
525 74.

526 De Vos, B., Van Meirvenne, M., Quataert, P., Deckers, J., Muys, B., 2005. Predictive quality
527 of pedotransfer functions for estimating bulk density of forest soils. *Soil Sci. Soc. Am. J.* 69,
528 500-510.

529 Elith, J., Leathwick, J.R., Hastie, T., 2008. A working guide to boosted regression trees. *J.*
530 *Anim. Ecol.* 77, 802-813.

531 Elith, J., Graham, C.H., et al., 2006. Novel methods improve prediction of species'
532 distributions from occurrence data. *Ecography* 29, 129-151.

533 Guisan, A., Edwards, T.C., Hastie, T., 2002. Generalized linear and generalized additive
534 models in studies of species distributions: setting the scene. *Ecol. Model.* 157, 89-100.

535 Guisan, A., Zimmermann, N.E., 2000. Predictive habitat distribution models in ecology. *Ecol.*
536 *Model.* 135, 147-186.

537 Hill, M., Mountford, J., Roy, B., Bunce, R., 1999. Ellenberg's indicator values for British
538 plants. Center for Ecology and Hydrology.

539 Iverson, L.R., Dale, M.E., Scott, C.T., Prasad, A., 1997. A GIS-derived integrated moisture
540 index to predict forest composition and productivity of Ohio forests (USA). *Landsc. Ecol.* 12,
541 331-348.

542 Jabiol, B., Brêthes, A., Ponge, J., Toutain, F., Brun, J., 2007. *L'Humus sous toutes ses formes*,
543 second ed. AgoParisTech, Nancy.

544 Jakeman, A.J., Letcher, R.A., Norton, J.P., 2006. Ten iterative steps in development and
 545 evaluation of environmental models. *Environ. Model. Softw.* 21, 602–614.

546 Jansen, J. J., Sevenster, J., Faber, P. J., 1996. Opbrengsttabellen voor belangrijke
 547 boomsoorten in Nederland. IBN-DLO, Wageningen.

548 Kangas, J., Hokkanen, J., Kangas, A.S., Lahdelma, R., Salminen, P., 2003. Applying
 549 Stochastic Multicriteria Acceptability Analysis to forest ecosystem management with both
 550 cardinal and Ordinal criteria. *Forest Sci.* 49, 928-937.

551 Kangas, J., Kangas, A., 2003. Multicriteria approval and SMAA-O method in natural
 552 resources decision analysis with both ordinal and cardinal criteria. *J. Multi-Criteria Decis.*
 553 *Anal.* 12, 3–15.

554 Kangas, J., Kangas, A., 2005. Multiple criteria decision support in forest management – the
 555 approach, methods applied, and experiences gained. *Forest Ecol. Manage.* 207, 133-143.

556 Kangas, A., Kangas, J., Lahdelma, R., Salminen, P., 2006. Using SMAA-2 method with
 557 dependent uncertainties for strategic forest planning. *Forest Policy Econ.* 9, 113-125.

558 Lahdelma, R., Hokkanen, J., Salminen, P., 1998. SMAA - Stochastic multiobjective
 559 acceptability analysis. *Eur. J. Oper. Res.* 106, 137-143.

560 Lahdelma, R., Salminen, P., 2001. SMAA-2: stochastic multicriteria acceptability analysis for
 561 group decision making. *Oper. Res.* 49, 444–454.

562 Leathwick, J.R., Elith, J., Francis, M.P., Hastie, T., Taylor, P., 2006. Variation in demersal
 563 fish species richness in the oceans surrounding New Zealand: an analysis using boosted
 564 regression trees. *Mar. Ecol.-Prog. Ser.* 321, 267-281.

565 Mckenney, D.W., Pedlar, J.H., 2003. Spatial models of site index based on climate and soil
 566 properties for two boreal tree species in Ontario, Canada. *Forest Ecol. Manage.* 175, 497-507.

567 Moisen, G.G., Freeman, E.A., Blackard, J.A., Frescino, T.S., Zimmermann, N.E., Edwards,
 568 T.C., 2006. Predicting tree species presence and basal area in Utah: a comparison of
 569 stochastic gradient boosting, generalized additive models, and tree-based methods. *Ecol.*
 570 *Model.* 199, 176-187.

571 Moisen, G.G., Frescino, T.S., 2002. Comparing five modelling techniques for predicting
 572 forest characteristics. *Ecol. Model.* 157, 209-225.

573 Muys, B., Granval, P., 1997. Earthworms as bio-indicators of forest site quality. *Soil Biol.*
 574 *Biochem.* 29, 323-328.

575 Ponge, J., Chevalier, R., Loussot, P., 2002. Humus index: an integrated tool for the
 576 assessment of forest floor and topsoil properties. *Soil Sci. Soc. Am. J.* 66, 1996-2001.

577 Segurado, P., Araújo, M., 2004. An evaluation of methods for modelling species distributions.
 578 *J. Biogeogr.* 31, 1555–1569.

579 Szwaluk, K.S., Strong, W.L., 2003. Near-surface soil characteristics and understory plants as
 580 predictors of *Pinus contorta* site index in Southwestern Alberta, Canada. *Forest Ecol.*
 581 *Manage.* 176, 13-24.

582 Teepe, R., Dilling, H., Beese, F., 2003. Estimating water retention curves of forest soils from
 583 soil texture and bulk density. *J. Plant Nutr. Soil Sci.* 166, 111-119.

584 Tervonen, T., Figueira, J.R., 2008. A survey on stochastic multicriteria acceptability analysis
 585 methods. *J. Multi-Criteria Decis. Anal.* 15, 1-14.

586 Tervonen, T., Lahdelma, R., 2007. Implementing stochastic multicriteria acceptability
587 analysis. *Eur. J. Oper. Res.* 178, 500-513.

588 Tervonen, T., 2010. JSMAA: an open source software for SMAA computations, in:
589 Henggeler Antunes, C., Rios Insua, D., Dias, L.C. (eds.), *Proceedings of the 25th mini EURO*
590 *conference on uncertainty and robustness in planning and decision making (URPDM2010)*,
591 *Coimbra*.

592 Thuiller, W., Lafourcade, B., Engler, R., Araújo, M.B., 2009. BIOMOD – a platform for
593 ensemble forecasting of species distributions. *Ecography* 32, 369-373 (version 0).

594 Wang, Y.H., Raulier, F., Ung, C.H., 2005. Evaluation of spatial predictions of site index
595 obtained by parametric and nonparametric methods - a case study of Lodgepole pine
596 productivity. *Forest Ecol. Manage.* 214, 201-211.

Table 1. Summary of the site characteristics in Flanders stratified according to the three studied tree species

Variable	Pedunculate oak (n=76)			Common beech (n=55)			Scots pine (n=55)		
	Mean (S.D.)	Min.	Max.	Mean (S.D.)	Min.	Max.	Mean (S.D.)	Min.	Max.
Site index (m)	28.98 (3.93)	20.61	36.61	37.77 (4.45)	26.21	43.57	24.07 (4.24)	15.81	35.32
Elevation (m)	52 (43)	8	129	62 (39)	8	125	45 (27)	8	127
TRASP	0.46 (0.35)	0	1	0.48 (0.36)	0	1	0.49 (0.37)	0	1
Slope (%)	1.3 (1.9)	0	9.7	2.7 (4.2)	0.1	25	1.1 (1.6)	0	7.3
Curvature	0.03 (0.23)	-0.63	0.61	-0.02 (0.27)	-1.02	0.67	0.09 (0.25)	-0.47	0.74
Flow accumulation (m ²)	228 (792)	0	6175	2067 (10402)	0	75275	705 (3861)	0	28525
Late frost days	1.65 (0.57)	0.5	2.91	1.36 (0.41)	0.5	2	2.03 (0.77)	0.5	3.22
Hill mF	5.91 (0.60)	5.03	7.87	5.39 (0.36) ^a	5.00	6.33	5.77 (0.73)	5.01	7.9
Hill mN	5.04 (0.98)	2.22	6.08	4.92 (0.95) ^a	3	7	3.66 (0.96)	2.1	5.97
Hill mR	5.03 (0.92)	2.54	6.53	4.74 (0.66) ^a	3	6	3.40 (0.98)	2.06	5.97
Hill mL	5.58 (0.60)	4.22	6.9	4.87 (0.79) ^a	3	5.99	6.03 (0.42)	5.18	6.95
Hill mN*mR	26.18 (8.61)	7.02	39.57	23.53 (6.23) ^a	9	35.94	13.24 (7.53)	6.20	35.64
Humus form	5.93 (1.25)	4	9	6.69 (0.97)	5	9	7.50 (1.15)	5.25	9
sd Humus form	0.54 (0.37)	0	1.63	0.86 (0.40)	0	2	0.73 (0.52)	0	1.88
Humus thickness (cm)	5.49 (2.33)	0	12	5.42 (2.16)	1	13	8.62 (2.88)	4	16
Ah thickness (cm)	4.82 (4.67)	0	21.06	2.91 (2.00)	0.06	11.69	4.05 (3.88)	0	18.75
Soil depth (cm)	46.40 (10.67) ^b	17.44	71.44	53.10 (12.34) ^c	32.56	78.12	42.16 (13.83) ^d	21	67.81
Clay (%)	16.59 (7.89)	4.18	31.1	17.15 (8.73)	4.79	30.8	7.86 (5.64)	1.85	21.7
Silt (%)	28.70 (20.58)	3.18	64.7	34.53 (20.50)	4.91	65.8	12.21 (11.33)	1.9	50.4
Sand (%)	54.71 (27.75)	8.36	92.66	48.33 (29.13)	5.33	89.57	79.93 (16.72)	27.89	96.18
Soil pH	3.59 (0.17)	3.24	4.14	3.64 (0.11)	3.31	3.93	3.53 (0.21)	3.1	3.95
Soil OM (%)	4.18 (1.38)	1.24	8.13	3.81 (0.94)	1.71	6.38	2.84 (1.14)	0.97	5.2
Soil N (%)	0.12 (0.04)	0.04	0.28	0.10 (0.02)	0.05	0.18	0.07 (0.03)	0.03	0.15
Soil C:N	19.07 (4.12)	9.91	39.6	22.39 (3.11)	17.22	29.67	24.28 (7.86)	13.5	54
Bulk density (g/cm ³)	1.41 (0.07)	1.23	1.58	1.43 (0.05)	1.3	1.55	1.18 (0.06)	1.36	1.59
AWC	0.19 (0.01)	0.16	0.2	0.19 (0.01)	0.16	0.21	0.17 (0.01)	0.16	0.2
AC	0.14 (0.05)	0.04	0.22	0.13 (0.06)	0.04	0.21	0.18 (0.03)	0.08	0.22
PWP	0.14 (0.05)	0.06	0.22	0.15 (0.05)	0.07	0.23	0.09 (0.03)	0.05	0.18

N deposition	6.88 (1.37)	5	9	7.02 (1.59)	5	9	7.20 (1.33)	5	9
Drainage	3.77 (1.48)	1	6	3.18 (1.18)	2	7	2.82 (1.31)	1	5

^a Based on only 43 observations (12 plots without vegetation)

^{b,c,d} Measured in respectively only 53, 45, 35 research plots

Table 2. Ordinal scores from 1 (most preferred) to 5 (least preferred) of the modelling techniques for the qualitative criteria of the SMAA

Alternative	Ecological interpretability	User-friendliness
MLR	3	2
CART	4	1
BRT	2	3
GAM	1	4
ANN	5	5

Table 3. Overview of the predictor variables present in the site index models for Flanders developed with five techniques

Tree species	Modelling technique	Variables present in the model
Pedunculate oak (n= 76)	MLR	Humus thickness, Sand, Soil C:N, mN*mR, Flow accumulation
	CART	Humus thickness, Clay, PWP, Late frost days
	BRT	Humus thickness, Sand, Clay, Soil C:N, PWP, mN*mR
	GAM	Humus thickness, Silt, Soil C:N, Soil OM, AWC, mN
	ANN	Humus thickness, Sand, Soil C:N, mR
Common beech (n=55)	MLR	Humus thickness, Humus form, Silt, Curvature, Flow accumulation, Ah thickness, Soil pH, AWC
	CART	Silt, Soil pH, mN
	BRT	Ah thickness, Silt, Clay, Soil pH, AC, mF
	GAM	Soil pH, Silt, Soil OM, Humus form, Humus thickness, Ah thickness, Curvature, N deposition, Drainage
	ANN	Soil pH, Silt, Sand, Soil OM, Humus thickness, N deposition
Scots pine (n=55)	MLR	Silt, Soil N, Ah thickness, N deposition
	CART	N deposition, Late frost days
	BRT	Silt, Clay, N deposition, mN*mR, mF
	GAM	Sand, Soil OM, Humus form, Humus thickness, Ah thickness, N deposition
	ANN	Sand, Soil OM, Humus form, Ah thickness, N deposition

Table 4. Performance indices of all site index models for the three tree species in Flanders and five modelling techniques: multiple linear regression (MLR), classification and regression trees (CART), boosted regression trees (BRT), generalized additive models (GAM) and artificial neural networks (ANN). Performance indices used in the MCDA are highlighted in bold, whereas best model performance for every index, based on the validation data, is underlined.

Performance index	MLR		CART		BRT		GAM		ANN	
	Calibration	Validation	Calibration	Validation	Calibration	Validation	Calibration	Validation	Calibration	Validation
<i>Pedunculate oak</i>										
R ²	0.44	0.25	0.60	0.22	0.58	0.29	0.47	0.32	0.58	<u>0.43</u>
CE	0.44	0.14	0.60	0.18	0.54	0.29	0.47	0.30	0.58	<u>0.42</u>
RMSE	2.93	3.62	2.47	3.54	2.65	3.29	2.84	3.26	2.54	<u>2.97</u>
RRMSE	0.10	0.12	0.09	0.12	0.09	0.11	0.10	0.11	0.09	<u>0.10</u>
AIC	91.65	107.76	76.77	104.04	86.15	102.44	91.26	<u>101.71</u>	94.94	106.72
BIC	103.30	119.41	86.09	<u>113.36</u>	100.14	116.42	105.24	115.70	122.91	134.69
R²adj	0.40	0.20	0.58	0.17	0.54	0.23	0.43	0.26	0.49	<u>0.32</u>
<i>Common beech</i>										
R ²	0.70	0.47	0.66	0.29	0.79	0.51	0.81	0.57	0.85	<u>0.60</u>
CE	0.70	0.46	0.65	0.13	0.79	0.51	0.81	0.55	0.85	<u>0.60</u>
RMSE	2.42	3.25	2.60	4.11	2.04	3.08	1.94	2.96	1.68	<u>2.80</u>
RRMSE	0.07	0.09	0.07	0.12	0.06	0.09	0.06	0.09	0.05	<u>0.08</u>
AIC	64.70	80.77	58.53	83.70	51.15	<u>73.87</u>	54.57	77.75	64.60	92.69
BIC	80.75	96.83	64.55	89.72	63.19	<u>85.92</u>	72.63	95.81	100.73	128.83
R²adj	0.66	0.40	0.64	0.25	0.77	0.45	0.77	<u>0.48</u>	0.78	0.40
<i>Scots pine</i>										
R ²	0.62	0.44	0.59	0.14	0.77	0.58	0.70	0.60	0.86	<u>0.66</u>
CE	0.62	0.43	0.59	-0.02	0.76	0.58	0.70	0.60	0.86	<u>0.65</u>
RMSE	2.57	3.19	2.68	4.24	2.06	2.73	2.30	2.66	1.60	<u>2.48</u>
RRMSE	0.11	0.13	0.11	0.18	0.09	0.11	0.10	0.11	0.07	<u>0.10</u>
AIC	59.99	71.71	58.18	83.49	49.68	<u>65.22</u>	57.81	65.90	55.70	79.91
BIC	68.02	79.74	62.20	87.50	59.71	<u>75.26</u>	69.85	77.94	85.81	110.02
R²adj	0.59	0.39	0.58	0.10	0.74	0.54	0.66	<u>0.55</u>	0.80	0.53

R^2 = Coefficient of determination, CE = Coefficient of Efficiency, RMSE = Root mean squared error, RRMSE = relative RMSE, AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, R^2_{adj} = adjusted R^2 .

Table 5. Rank acceptability indices, holistic acceptability indices (using centroid meta-weights) and confidence factors of all alternative techniques

		Holistic acceptability index	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Confidence factor
Pedunculate oak (Flanders)	ANN	0.64	0.45	0.14	0.22	0.19	0.01	1.00
	BRT	0.59	0.21	0.50	0.29	0.01	0.00	0.99
	GAM	0.54	0.26	0.28	0.23	0.23	0.00	1.00
	CART	0.33	0.09	0.09	0.26	0.55	0.02	0.71
	MLR	0.09	0.00	0.00	0.00	0.03	0.97	1.00
Common beech (Flanders)	GAM	0.87	0.71	0.27	0.01	0.00	0.00	1.00
	BRT	0.63	0.23	0.63	0.14	0.00	0.00	0.85
	ANN	0.31	0.04	0.09	0.41	0.34	0.13	1.00
	MLR	0.27	0.00	0.01	0.44	0.54	0.01	0.14
	CART	0.11	0.01	0.00	0.01	0.11	0.87	0.31
Scots pine (Flanders)	BRT	0.77	0.50	0.46	0.04	0.00	0.00	0.89
	GAM	0.64	0.31	0.43	0.25	0.01	0.00	0.70
	ANN	0.45	0.18	0.10	0.50	0.20	0.02	1.00
	MLR	0.23	0.00	0.01	0.21	0.78	0.01	0.16
	CART	0.10	0.00	0.00	0.00	0.02	0.97	0.28
Site index (Flanders and Turkey)	GAM	0.61	0.40	0.22	0.16	0.13	0.09	0.58
	BRT	0.53	0.23	0.33	0.23	0.14	0.06	0.31
	ANN	0.43	0.19	0.19	0.20	0.19	0.23	0.35
	MLR	0.33	0.07	0.16	0.26	0.31	0.20	0.10
	CART	0.29	0.11	0.09	0.15	0.23	0.42	0.38

598

Table 6. Mean values (standard deviation) of the quantitative criteria for all alternative techniques based on site index models for six different tree species in two ecoregions (Temperate lowland and Mediterranean mountains).

Criteria were scaled assuming a Gaussian distribution, with highest preference for RMSE and AIC closest to zero, whereas for R^2 and R^2_{adj} closest to unity.

Alternative	RMSE	AIC	R^2_{adj}	R^2
MLR	3.62 (0.34)	84.03 (14.39)	0.25 (0.13)	0.49 (0.15)
CART	4.13 (0.37)	86.82 (10.85)	0.16 (0.09)	0.49 (0.19)
BRT	3.40 (0.46)	80.68 (14.47)	0.31 (0.16)	0.63 (0.13)
GAM	3.25 (0.43)	88.12 (27.5)	0.36 (0.13)	0.58 (0.17)
ANN	2.98 (0.39)	94.72 (9.03)	0.29 (0.28)	0.76 (0.11)
<i>Scale</i>	[2.22 – 4.86]	[34.22 - 142.02]	[-0.26 – 0.84]	[0.12 – 0.98]

601 **Figure 1.** Location of the sample plots in Flanders, Belgium. Sample plots are labelled
602 according to the dominant tree species (■ Common Beech, ● Pedunculate oak, ▲ Scots pine).

Figure 2. Central weight vectors of the different alternatives based on the SMAA for pedunculate oak (A), common beech (B), Scots pine (C) in Flanders and species-independent (D) site index modelling in Flanders and Turkey.