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Modelling forest growing stock from inventory data: A data mining approach

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ABSTRACT

Growing stock is an ecological indicator of forest ecosystem response to natural and anthropogenic impacts that may result from forest management measures or environmental impacts. Information on growing stock is thus essential to understand dynamics of forest stands, their productive capacity and to manage their use within limits of sustainability. Dynamic changes of forest growing stock, as well as predictions of their future development, are usually estimated from the data gathered by national forest inventories using some mechanistic modelling approach. The resulting models are informative, but include many parameters, some of which are difficult to set or estimate. Due to the demanding parameterisation of mechanistic models, it is hard to achieve stability of their output accuracy, which can lower their predictive power. This paper presents an alternative and complementary approach of constructing models with machine learning and data mining methods. We applied these methods to the Silva-SI database and used the resulting interpretable models in order to find explanations for structural changes in Slovenian forests over the period from year 1970 to 2010. In addition, we developed predictive models for growing sock in the decade from year 2010 to 2020. The structure of the models describing temporal dynamics of growing stock shows that trends of growing stock are increasing for the entire studied period, while accumulation of growing stock is much more intensive after 1990. Forests with a lower growing stock are located either in the areas with non-favorable site conditions for forest growth, or at lower altitudes, where they are more exposed to human exploitation due to their vicinity to more densely populated regions. Predictions of growing stock for the decade 2010–2020 suggest that Slovenian forests will continue to accumulate their growing stock (private owned forests to 327 m^3/ha and state owned forests to 343 m^3/ha in 2020). The presented data mining approach that was here applied to the growing stock can also be used for investigating other ecological indicators.

1. Introduction

European forest resources are changing noticeably. Forest area in Europe (including European part of the Russian Federation) has expanded by 17 million ha during the past 20 years and the growing stock has increased by 8.600 million m^3 in the same period (SOEF, 2011). Forest in Slovenia is no exception and followed this trend with an increase of forest area available for wood supply by 5% (from 1.114 million ha in 1990 to 1.175 million ha in 2010) and growing stock of forests available for wood supply by 52% (from 256.3 million m^3 in 1990 to 389.9 million m^3 in 2010) (SOEF, 2011).

Magnitude and direction of changes of forest resources depend on a complex interplay between biological processes, abiotic constraints, initial state of forest stands and different natural and anthropogenic disturbances from both, controlled management, and other uncontrolled human induced activities. An initial state of forest stands and an applied forest management practice might be the two most important factors explaining changes in the forest structure and composition over shorter periods (a few decades) of time, while the impact of natural and social factors is indirect, through the differing conditions for forest management (Poljanec, 2008; Klopčič and Bončina, 2011).

Progress toward sustainable forest management can be assessed through the use of indicators as measures that provide information about potential or realized effects of human activities on forests. They are widely used on the national and international level such as in the Montreal Process of developing criteria and indicators for the conservation and sustainable management of temperate and boreal forests (Montreal Process, 2013) and in the Pan-European process of developing indicators for sustainable forest management in Europe and Russian Federation (State of Europe's Forests, 2011). In the suite of ecological indicators describing structural, compositional and functional characteristic of forests, growing stock plays

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a central role. Growing stock is one of the basic statistics of any forest inventory (Tomppo et al., 2010) and as such an indicator useful for various purposes. It is a fundamental element in determining the productive capacity of the area identified as forest available for wood production. Knowledge of a growing stock of the various tree species and its spatio-temporal dynamics is central to considerations of a sustainable supply of wood for products and the sustainability of the overall ecosystems. Growing stock can, by applying biomass expansion factors, be converted into estimates of above and below-ground woody biomass (e.g., Brown et al., 1999). Data on growing stock, increment and fellings are crucial for the calculation of carbon budgets in the forest sector (e.g., Karjalainen et al., 2003). Furthermore growing stock is also an important and well-accepted proxy for biodiversity.

It refers the properties that operate at a system level, including the appropriate species composition and the suitable environmental conditions that support processes of forest growth and development in particular and ecological integrity in general. Therefore growing stock can be attributed as an ecological indicator at system level which makes it particularly useful for forest management purposes. It is an indicator of forest ecosystem response to natural and anthropogenic impacts that may result from forest management measures or environmental impacts because it aggregates other state and stress indicators of forest ecosystem (i.e., quality of the soil, rainfall, temperature, growing stock increment, annual cut). Because of its systemic and integrative features, a growing stock can be used to assess the conditions of the forest, to diagnose the cause of structural or functional changes and to be used to predict future changes or trends of growing stock.

If the growing stock should be used for forest management on objective way, it has to diminish the three main methodological problems of use of indicators as a resource management tools (Dale and Beyeler, 2001): (i) too small number of indicators which are used to deal with complex ecological systems; (ii) problem of the selection of indicators which will enable understanding of the short-term, and long-term consequences of resource management decisions and (iii) difficulty with the interpretation of information provided with those indicators.

The dynamic changes of forest growing stock, as well as the predictions of their future development, at both European and national levels, are usually estimated from the data gathered by national forest inventories (Brassel and Brändli, 1999; Küchli et al., 1999; Risser, 2000) or, more rarely, by archival forestry data (e.g., Linder and Östlund, 1998; Axelsson et al., 2002; Ficko et al., 2011; Klopčič and Bončina, 2011). The European Forest Sector Outlook Study II (EFSOS, 2011) makes projections of European forest resources for a period from 2010 to 2030 and gives predictions of dynamic changes of forest resources at European and national levels. If no major policies or strategies are changed ("business-as-usual" scenario) in the European forest sector, the total forest area will increase by 6% (to 216.9 million ha in 2030) and the growing stock in the forest area available for wood supply will increase by 12% (from 174 m^3/ha in 2010 to 195 m^3/ha in 2030). The European Forest Sector Outlook (EFSOS, 2011) predictions for Slovenia show that the forest area available for wood supply will increase by 3% (from 1.175 million ha in 2010 to 1.211 million ha in 2030) and growing stock by 6% (from 334 m^3/ha in 2010 to 353 m^3/ha in 2030).

Predictions of the European Forest Sector Outlook Study II (EFSOS, 2011) are based on the results of several different modelling approaches. In particular, they respect outputs from econometric projections for production and consumption of forest products (Postma and Liebl, 2005; Arets et al., 2011), analysis of wood resource balance (Mantau et al., 2010), the results of the European Forest Information Scenario Model (EFISCEN) (Pussinen et al., 2001), and results of the European Forest Institute-Global Forest Sector Model (EFI-GTM) (Kallio et al., 2004, 2006). However, the majority of European countries have also developed their own tools for predicting dynamic forest changes at their national levels (e.g., Nabuurs et al., 1998). Common approaches to estimating and predicting future development of forest resources employ various methods, ranging from static inventory projections, to complex techniques of modelling. Such induced models usually project future forest development by using national forest inventory and yield data under some strong assumptions, like that the uncertainty of future growth is small and insignificant, or that the forest management doesn't change in time (Mohren, 2003). In some countries, detailed inventory and yield data are not available for sufficiently long periods of time (i.e., a few decades), and therefore, such models cannot be constructed.

Due to the large changes of forest stand structure (e.g., growing stock, forest area, tree species composition) noticed over the last few decades and changing climate and management objectives, improved spatio-temporal models for predicting changes of forest stand structure are required. These would not only provide a better insight into the complex interplay of growing and management conditions, but would also provide predictions of their future trends, which is necessary for improving forest policies, planning and decision making in order to ensure economically and ecologically sound forest management, and to reduce the risks due to the forecasted environmental changes. In addition, accurate predictions of future development of forest resources (e.g., growing stock, annual increment, etc.) are required for reporting carbon stocks and stock changes at national levels in accordance with the Kyoto protocol (Muukkonen and Heiskanen, 2005).

The most frequently used approach for predicting dynamic changes of forest resources is based on the modelling of forest variables among which the growing stock presents the most central one. This modelling task is usually based on mechanistic modeling approach, where the field data are used for calibration and validation of such models, while the models' structure is based on theoretical knowledge. Such an approach is informative, but includes many parameters, some of which are difficult to set or estimate. It often requires many different types of data that are not always possible to obtain (i.e., crown ratio, regeneration). Due to the large number of parameters that have to be fitted in mechanistic models, it is hard to achieve stability of output accuracy, which might also lower their predictive power (Jørgensen and Bendoricchio, 2001). In this context, dynamic changes of forest variables (e.g., the growing stock) are modeled using mechanistic modeling approaches that are based on: (i) patch (gap) models that operate at a different level of physiological detail of structural and compositional dynamics of forest ecosystem (simulation of forest succession, species distribution (e.g., PICUS (Jäger et al., 2004)), or under a wide range of environmental and management conditions (e.g., FORCLIM (Rasche et al., 2012)); (ii) individual-based models that explore various management and environmental effects on the ecological, structural and spatial dynamics of forest (e.g., MOSES (Hasenauer, 1994), CAPSIS (Dufour-Kowalski et al., 2012), iLand (Seidl et al., 2012)); and (iii) spatially explicit forest landscape models that simulate spatial projections of forest derived ecosystem services, and evaluate how these services will be impacted under future climate disturbance and management scenarios (e.g., LANDCLIM (Schumacher et al., 2004), LANDIS II (Scheller et al., 2007; Scheller and Mladenoff, 2007)).

In this paper we present a novel approach for predicting temporal dynamic changes of growing stock that can be regarded as an alternative or a complement to the above mentioned mechanistic approach. It is based on the application of machine learning and data mining methods to the forest inventory data. These methods can automatically generate (or learn or induce) models from existing historical data, and can therefore significantly accelerate and simplify the modelling process. They combine different techniques from statistics, computer science and information theory (Mitchell, 1997; Witten et al., 2011). In addition, they can efficiently find regularities and patterns in large databases, something that is virtually impossible for human modellers. In the end, when the automatically induced models are interpreted and combined with expert's knowledge, we can acquire analysis results of a higher quality and gain new insights into the investigated topic. In the area of life sciences, machine learning tools have already been successfully used for data analysis and learning of qualitative and quantitative models from data with many applications in the field of environmental and agricultural sciences (Debeljak et al., 2007, 2008, 2011, 2012; Trajanov et al., 2008, 2009; Trajanov, 2011), and also some applications in forestry (Stojanova et al., 2010, 2012; Ogris and Jurc, 2010).

We apply inductive machine learning techniques to available forest inventory data and yield data, in order to find explanations for structural changes in Slovenian forests over the period from year 1970 to 2010, and to develop predictive models for growing sock in the decade from 2010 to 2020. We focus on the analysis of the spatio-temporal dynamics of growing stock and we develop models that enable us to diagnose changes of growing stock, as well as to predict the growing stock accumulation in the next decade. This is a new methodological approach for explaining changes of a system level ecological indicator of forest conditions and for predicting its future development, and as such complements the classic mechanistic modelling methodologies.

2. Study area

Slovenian forests grow under a large variety of natural conditions, reflected in latitudinal and altitudinal zonation of vegetation, which is further reflected in a variety of different management techniques practiced in different areas. Starting from year 1970, the data show evident changes in the accumulation of growing stock (from 190 m^3/ha to 294 m^3/ha in 2010), in the increase of annual increment (from 4.1 m^3/ha to 6.7 m^3/ha in 2010), in the decreasing share of small-diameter trees (dbh < 30 cm; from 49% of total growing stock in 1970 to 31% in 2010), and in the increasing shares of medium-diameter (30 cm ≤ dbh < 50 cm) and large-diameter trees (dbh ≥ 50 cm; from 43% to 46% and from 9% to 18% of total growing stock) (Poljanec and Bončina, 2010). Furthermore, the tree species composition of forests has also changed considerably. The changes are reflected in the higher share of broadleaves (rising from 40% of total growing stock in 1970 to 48% in 2008), principally beech (Poljanec et al., 2010), and the reduction of conifers, especially silver fir (Ficko et al., 2011). Observed changes in growing stock could be mainly explained by forest management objectives which were oriented toward the accumulation of stands' volume increment after heavy exploitation in the first decades after the World War II rather than by the implementation of different inventory methods with variable accuracy and disparities between regions within the study area.

The study was conducted on 64% of the entire forest area of Slovenia (Fig. 1) for which georeferenced and harmonized data for the period from year 1970 to 2010 exist. The underlying characteristic of the study area is a considerable variation of relief and climatic conditions. The mean annual precipitation decreases from the west to the east. In general, a similar pattern can be observed for temperature, but the elevation is an additional factor that significantly influences the temperature. The forests in the study area are characterised by a small-scale management system, using irregular shelterwood and group systems. At the last forest inventory (SFS, 2010), the mean growing stock at the area included in the study amounted to 302 m^3/ha and the mean annual increment was 6.7 m^3/ha. There were 46 different tree species recorded in the study area; Norway spruce (32%) and European beech (31%) accounted for the highest proportion of growing stock, followed by silver fir (8%).

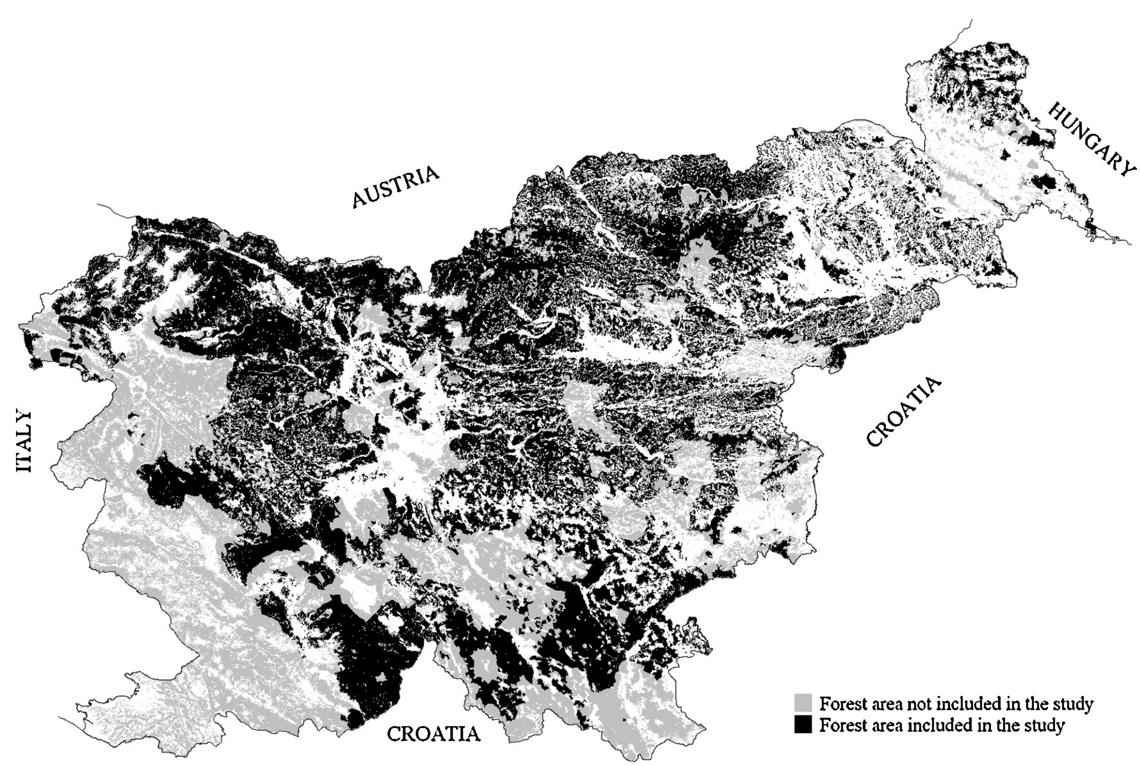


Fig. 1. The location of the study area.

2.1. Data set

Data for the research were provided by the spatial information database Silva-SI (Poljanec, 2008), which collects data from various sources, mostly forest inventories within Forest Management Plans (FMP), which are typically performed every 10 years (each year approximately 1/10 of FMP are revised). The database currently comprises digitalised data for 21,052 forest compartments covering 7452 km^2 or 64% of the Slovenian forests for the period from the year 2010 back to 1970 (Fig. 1). Digitalisation of older data is under way, but it is not yet completed and therefore data from before the year 1970 were not included in our study. Forest compartments are permanent and their size and borders have not been changed since the first forest inventories. All compartments are described with the same suite of total 47 environmental variables and stand variables which indicate the state of forest stands (Table 1). The variables describing geographic characteristics of compartments (INC, INC_SD, ELV, ELV_SD and ASP) were acquired from a digital elevation model with a spatial resolution of 25 m × 25 m. A variation of the aspect on each compartment (ASP_VAR) was calculated as the Shannon-Wiener index (Pielou, 1975) based on data obtained from the same digital elevation model. The surface stoniness and rockiness (ROC), and the type of bedrock (BEDR) were estimated in the field. The climatic variables were calculated from 100 m resolution raster maps of the mean annual temperature (T) and the mean annual precipitation (PREC) (ARSO, 2004a,b). Each compartment was also classified into European forest categories (FT) following the procedure described by Matijasic and Boncina (2006) and located into one of the six phyto-geographical regions to which Slovenian forests belong (PHYTOREG). Forests within the specific phyto-geographical region have uniform climatic conditions and distinctly recognisable type and structure of vegetation. Site productivity within the compartments was ranked on the scale from 1 to 17, according to the methodology proposed by Košir (2002), where the most productive compartment gets rank 17 and the least productive one gets rank 1 (PI). Depending on the proportion of the state ownership (OWN) in a given compartment, two groups of compartments were formed: a "state owned" forest, were the compartment is 100% owned by the state (5237 compartments), and a "private owned" forest, where the proportion of the state ownership is less than 100% (15,815 compartments). Since the compartment may consist of forest parcels belonging to different owners, the average size of forest parcel for each compartment is also given (PARC). The stand variables, indicating state of forest stands within the compartments such as growing stock (GS) and annual increment (I) were estimated at 10 years time steps with the official methodology of forest inventories, which is approved and applied by the Slovenian Forestry Service. Forest inventories contain a combination of field descriptions of all stands and tree measurements (dbh ≥ 10 cm) at permanent 500 m^2 sampling plots with a dominant sampling network size of 250 m × 500 m (SFS, 2010, Kovač et al., 2009).). The proportion of three main tree species (Norway spruce *Picea abies* Karst., silver fir *Abies alba* Mill. and European beech *Fagus sylvatica* L.) in the growing stock of forest stands (P_NS, P_SI, P_EB) is also given as an additional state indicator. The last variable in the data set is the planned annual cut (E) in each compartment, as specified by the FMP, which indicate the intensity and strategy of forest management in the coming/next/future management period. We assumed that the realisation of the planned cut was 100% in the state owned compartments, while its realisation in private forests is usually lower and at the compartment level cannot be reliably estimated.

2.2. Methods

Dynamic changes of the growing stock within forest compartments were analysed with machine learning methods (Mitchell, 1997). In general, we were looking for possible explanations of associations between the growing stock and other state indicators and environmental variables (e.g., climate and geographic variables). More specifically, to make a diagnosis of growing stock changes through time, we used decision tree learning methods, because they produce interpretable models, as opposed to most of other nonlinear modelling procedures, which produce models that are hard to interpret (so-called black box models).

Decision trees (Breiman et al., 1984) are hierarchical models, where each internal node contains a test on a descriptive attribute of an example (in our case a compartment) and each branch leaving this node corresponds to an outcome of this test. Terminal nodes (leaves) of a tree contain models defining the values of the dependent variable for all examples falling in a given leaf. Given a new example, for which the value of the dependent variable should be

Table 1
Variables used for modelling the forest stand structure.

Name	Description
FMC	Forest management compartment
AREA	Forest area in compartment (ha)
ELV	Mean elevation (m.a.s.l.)
ELV_SD	Standard deviation of elevation (m.a.s.l.)
INC	Mean inclination (°)
INC_SD	Standard deviation of elevation (°)
ASP	Prevailing aspect of the compartment (flat, N, NE, E, SE, S, SW, W, NW)
ASP_VAR	Variation of aspect (Shannon-Wiener index)
T	Mean annual temperature (°C)
PRECEP	Mean annual precipitation (mm)
ROC	Surface stoniness and rockiness (%)
BEDR	Bedrock: 1 – carbonate; 2 – non-carbonate
FT	Forest types
PHYTOREG	Phyto-geographical regions: 1 – alpine, 2 – prealpine, 3 – dinaric, 4 – predinaric, 5 – subpanonian, 6 – mediterranean
PI	The site productivity index within the compartment (1 – the lowest productivity, 17 – the highest productivity).
OWN	Ownership: state owned (100%), private owned (less than 100% state owned)
PARC	The average size of forest parcels in the compartment (ha)
GS70, GS80, GS90, GS00, GS10	Growing stock in years 1970, 1980, 1990, 2000, 2010 (m^3/ha)
I70, I80, I90, I00, I10	Average annual increment in years 1970, 1980, 1990, 2000, 2010 (m^3/ha/year)
P_NS70, P_NS80, P_NS90, P_NS00, P_NS10	Proportion of Norway spruce in growing stock in years 1970, 1980, 1990, 2000, 2010 (%)
P_ SF70, P_ SF80, P_ SF90, P_SF00, P_SF10	Proportion of silver fir in growing stock in years 1970, 1980, 1990, 2000, 2010 (%)
P_EB70, P_EB80, P_EB90, P_EB00, P_EB10	Proportion of European beech in growing stock in years 1970, 1980, 1990, 2000, 2010 (%)
E70, E80, E90, E00, E10	Annual allowable cut in the period 1971–1980, 1981–1990, 1991–2000, 2001–2010, 2011–2020 (m^3/ha)

predicted, the tree is interpreted from the root. In each inner node, the prescribed test is performed, and according to the result, the corresponding sub-tree is selected. When the selected node is a leaf, the value of the dependent variable for the new example is predicted according to the model in this leaf. If the dependent variable is numeric, the models in the leaves are typically constant values (regression tree) or linear functions (model tree (Quinlan, 1992)). It is also possible for the dependent variable to be a structured object such as a vector or a time-series. In this case, the tree (called multi-target tree (Blockeel et al., 1998)) basically predicts several dependent variables simultaneously. The main advantage of multi-target trees (MTTs) over a set of separate trees for each dependent variable is that a single MTT is usually much smaller than the total size of the individual trees for all variables and therefore much easier to interpret. Once a decision tree is learned on the data we can use it for two purposes. First, we can use it for explaining the connections between the variables and determine the variables that are important for grouping (clustering) similar examples according to the dependent target variable. Second, we can use the tree for predicting the dependent variable of new examples, e.g., for predicting growing stock in the future.

We have performed two sets of investigations on both, private owned and state owned forests. The first part of the research was focused on determination of the main variables that influence the temporal dynamics of the growing stock throughout the study period 1970–2010. We employed the multi-target regression trees as implemented in the Clus data mining software (Blockeel and Struyf, 2002). Growing stock for all time points were set as dependent variables and all time independent variables from the data were set as the dependent (descriptive) variables. Induced multi-target trees gave prevailing types of the growing stock trends in the studied period.

In the second part of the study, models for predicting growing stock in the decade 2010–2020 were built as single-target model trees (Quinlan, 1992) with the Weka data mining software (Witten et al., 2011). Growing stock at a specific time point was used as a predicted variable, while the independent variables were all the variables from the data set, except the ones that would not have been known a decade before (e.g., for predicting growing stock in year 1990, we would include growing stock from years 1970 and 1980, and annual allowable cut for years 1970, 1980 and 1990). Predictive models for year 2020 were built in two steps. First, we learned a model tree (with linear functions of the independent variables in the leaves) for predicting growing stock in year 2010. Next, we took this model and kept its structure (tree and linear functions), but we exchanged time dependent variables annual allowable cut and growing stock for their analogues in the next decade. Finally, we corrected the constant terms in linear equations by taking into account the overall increasing trend of the growing stock values. We used simple linear extrapolation

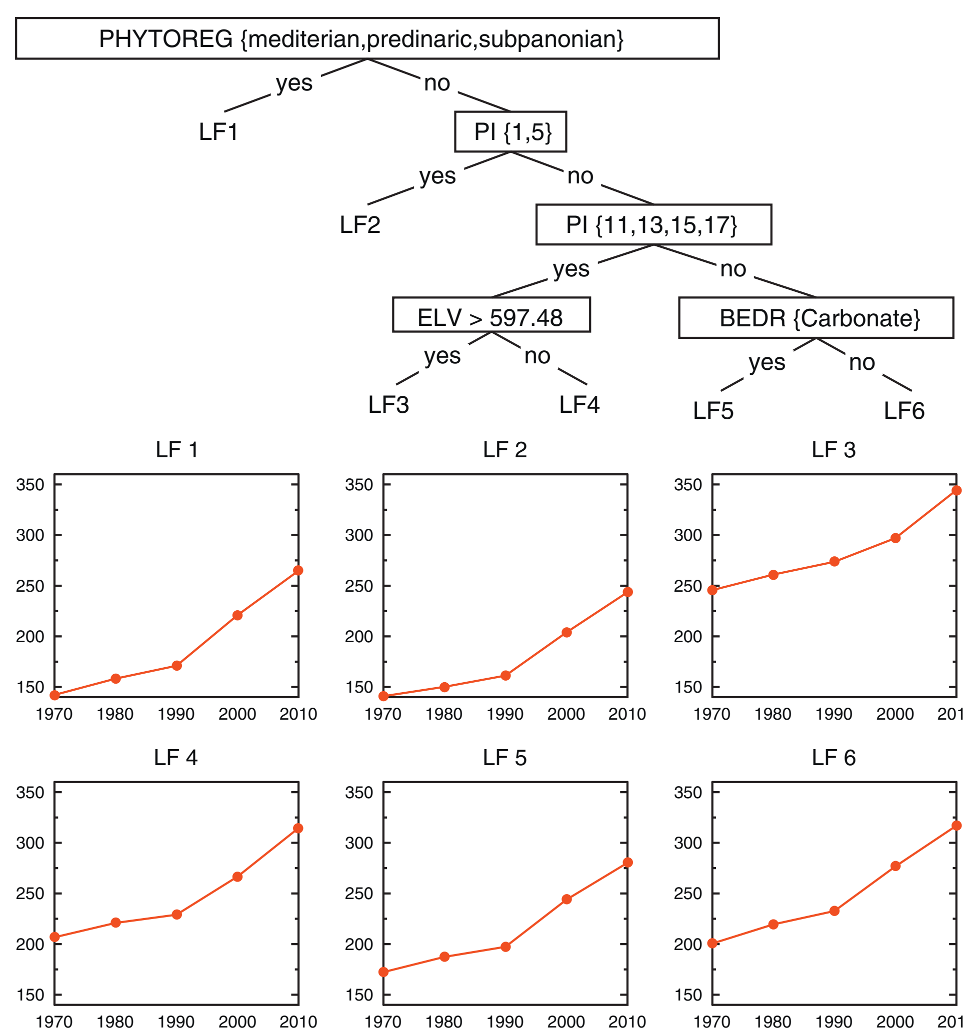


Fig. 2. The model describing dynamics of the growing stock changes in private owned forests. Evaluation results of the model using RMSE [1970, 1980, 1990, 2000, 2010], average: [65.7, 69.5, 66.5, 70.1, 71.0], 68.6.

from the values in the previous decades to estimate these corrections.

The induced models were evaluated using the root mean squared error (RMSE) estimated with 10-fold cross validation procedure. In cross-validation, we decide on a fixed number of folds, or partitions of the data. In our case, we used the number 10. Then, the data are split into 10 approximately equal partitions, each of which (in turn) was used for testing while the remainder of the data was used for training. This procedure was repeated 10 times so that, in the end, each partition has been used exactly once for testing. At the end, the obtained accuracies on the different iterations were averaged to yield an overall accuracy. In addition, the structure of the models was inspected, while taking into account the expected relationships between the elements of the model based on our existing knowledge.

3. Results

3.1. Modelling dynamic changes of growing stock

The structure of models describing the temporal dynamics of growing stock shows that the most important variables in private owned forests (Fig. 2) is phyto-geographic region (PHYTOREG), followed by site productivity index (PI), altitude (ELV) and bedrock (BEDR), while the topmost variable for state owned forest is site productivity index, followed by altitude and bedrock (Fig. 3). Forests with the highest growing stock can be found on sites with productivity index above 9, elevation above 600 m.a.s.l. (private owned forest) or 700 m.a.s.l. (state owned forest), and on non-carbonate bedrock, while forests with low growing stock are located on sites with low productivity index, low altitude and carbonate bedrock. All trends of growing stock are increasing nonlinearly, the growing stock increases faster after the year 1990. Regardless of the initial growing stock in 1970 and the absolute value of growing stock, none of the trends show any convergence to some target or maximal value. The absolute increase of the growing stock from 1970 to 2010 is very similar for all cases in the induced models, regardless of the forest ownership type and the value of the initial growing stock in 1970. The model evaluation shows that going from the first period (1970) to the present, the errors are decreasing for a model of state owned forests (RMSE decreased by 11.6%) and they stay approximately at the same level for a model of private owned forests.

3.2. Predicting growing stock in the next decade

As described in the Methods Section, prediction models for growing stock in the next decade (in year 2020) were constructed by first learning models for growing stock in year 2010 and then correcting them with overall growing stock trends. We therefore

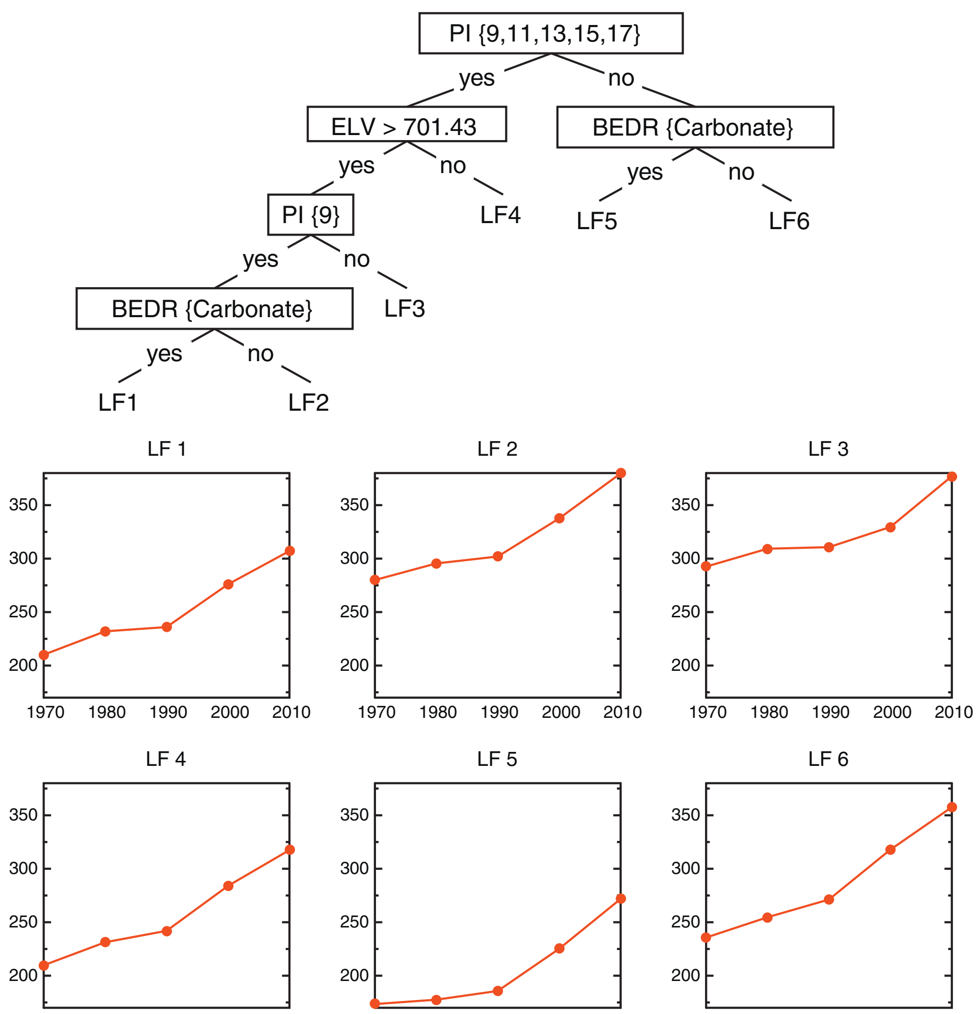
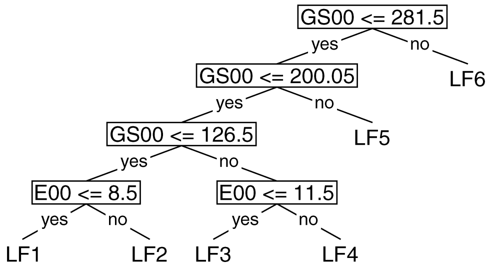


Fig. 3. The model describing dynamics of the growing stock changes in state owned forests. Evaluation results of the model RMSE [1970, 1980, 1990, 2000, 2010], average: [102.1, 100.5, 94.7, 91.4, 90.3], 95.9.

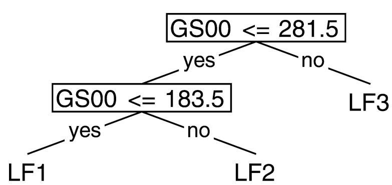


LF1: GS10 = -0.0001 * ELV - 0.0067 * INC + 0.6296 * (PHYTOREG= Alpine) + 0.8584 * (PHYTOREG=Prealpine, Dinaric) + 0.0014 * GS90 + 0.0629 * GS00 + 0.0005 * E70 - 0.0012 * E80 + 0.0212 * E90 + 0.1339 * E00 + 143.6339
LF2: GS10 = -0.0001 * ELV - 0.0067 * INC + 0.6296 * (PHYTOREG= Alpine) + 0.8584 * (PHYTOREG=Prealpine, Dinaric) + 0.0014 * GS90 + 0.0629 * GS00 + 0.0005 * E70 - 0.0012 * E80 + 0.0212 * E90 + 0.2473 * E00 + 182.253
LF3: GS10 = -0.0001 * ELV - 0.0067 * INC + 0.6296 * (PHYTOREG= Alpine) + 1.1241 * (PHYTOREG=Prealpine, Dinaric) + 0.0014 * GS90 + 0.6393 * GS00 + 0.0005 * E70 - 0.0012 * E80 + 0.0255 * E90 + 0.022 * E00 + 111.9608
LF4: GS10 = -0.0001 * ELV - 0.0067 * INC + 0.6296 * (PHYTOREG= Alpine) + 25.5005 * (PHYTOREG=Prealpine, Dinaric) + 0.0014 * GS90 + 0.2616 * GS00 + 0.0005 * E70 - 0.0012 * E80 + 0.0184 * E90 + 0.0161 * E00 + 193.5301
LF5: GS10 = -0.0001 * ELV - 0.0067 * INC + 24.0818 * (PHYTOREG= Alpine) + 23.9091 * (PHYTOREG=Prealpine, Dinaric) + 0.134 * GS90 + 0.5775 * GS00 + 0.0005 * E70 - 0.2274 * E80 + 0.283 * E90 + 0.0021 * E00 + 109.9682
LF6: GS10 = 0.0501 * ELV - 0.7055 * INC + 0.1896 * (PHYTOREG= Alpine) + 0.1057 * (PHYTOREG=Prealpine, Dinaric) + 0.0847 * GS90 + 0.6228 * GS00 + 0.0004 * E70 - 0.001 * E80 + 0.0006 * E90 + 0.0005 * E00 + 106.0139

Fig. 4. Model of the growing stock in state forests for 2010.

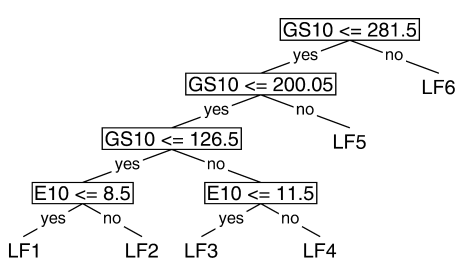
first present the models for year 2010 (Figs. 4 and 5), and then the corrections that were performed to adapt them to year 2020 (Figs. 6 and 7).

The structure of the growing stock model for state owned forests in 2010 (Fig. 4) shows that the growing stock in a previous period (GS00) has expectedly the greatest influence on the growing stock in 2010 (GS10). If the growing stock in 2000 is below 200 m^3/ha (the average in 2000 is 334.6 m^3/ha), then the growing stock in 2010 depends also on annual allowable cut of the previous period (E00). The lowest growing stock is estimated for compartments



LF1: GS10 = -0.0387 * ELV + 0.0845 * PI=11,3,7,15,17 + 0.0795 * (PHYTOREG=Prealpine, Alpine) + 0.0001 * GS70 + 0.2302 * GS90 + 0.6201 * GS00 + 120.3242
LF2: GS10 = 0 * ELV + 14.6206 * PI=11,3,7,15,17 + 15.1998 * (PHYTOREG=Prealpine, Alpine) + 0.0203 * GS70 + 0.2167 * GS90 + 0.3798 * GS00 + 127.4198
LF3: GS10 = 0.0399 * ELV + 10.8066 * PI=11,3,7,15,17 + 0.0283 * (PHYTOREG=Prealpine, Alpine) + 0.0001 * GS70 + 0.1484 * GS90 + 0.591 * GS00 + 80.9512

Fig. 5. Model of the growing stock in private forests for 2010.



LF1: GS20 = -0.0001 * ELV - 0.0067 * INC + 0.6296 * (PHYTOREG= Alpine) + 0.8584 * (PHYTOREG=Prealpine, Dinaric) + 0.0014 * GS00 + 0.0629 * GS10 + 0.0005 * E80 - 0.0012 * E90 + 0.0212 * E00 + 0.1339 * E10 + 217.530
LF2: GS20 = -0.0001 * ELV - 0.0067 * INC + 0.6296 * (PHYTOREG= Alpine) + 0.8584 * (PHYTOREG=Prealpine, Dinaric) + 0.0014 * GS00 + 0.0629 * GS10 + 0.0005 * E80 - 0.0012 * E90 + 0.0212 * E00 + 0.2473 * E10 + 291.237
LF3: GS20 = -0.0001 * ELV - 0.0067 * INC + 0.6296 * (PHYTOREG= Alpine) + 1.1241 * (PHYTOREG=Prealpine, Dinaric) + 0.0014 * GS00 + 0.6393 * GS10 + 0.0005 * E80 - 0.0012 * E90 + 0.0255 * E00 + 0.022 * E10 + 145.791
LF4: GS20 = -0.0001 * ELV - 0.0067 * INC + 0.6296 * (PHYTOREG= Alpine) + 25.5005 * (PHYTOREG=Prealpine, Dinaric) + 0.0014 * GS00 + 0.2616 * GS10 + 0.0005 * E80 - 0.0012 * E90 + 0.0184 * E00 + 0.0161 * E10 + 270.219
LF5: GS20 = -0.0001 * ELV - 0.0067 * INC + 24.0818 * (PHYTOREG= Alpine) + 23.9091 * (PHYTOREG=Prealpine, Dinaric) + 0.134 * GS00 + 0.5775 * GS10 + 0.0005 * E80 - 0.2274 * E90 + 0.283 * E00 + 0.0021 * E10 + 134.323
LF6: GS20 = 0.0501 * ELV - 0.7055 * INC + 0.1896 * (PHYTOREG= Alpine) + 0.1057 * (PHYTOREG=Prealpine, Dinaric) + 0.0847 * GS00 + 0.6228 * GS10 + 0.0004 * E80 - 0.001 * E90 + 0.0006 * E00 + 0.0005 * E10 + 114.531

Fig. 6. Model of the growing stock in state forests for 2020.

with the lowest annual allowable cut. Such compartments are likely to consist of the forest in younger development stages. Remarkably, variables describing habitat conditions do not appear in the structure of the model. Root mean squared error (RMSE) estimated with 10-fold cross validation is 60.65 m^3/ha.

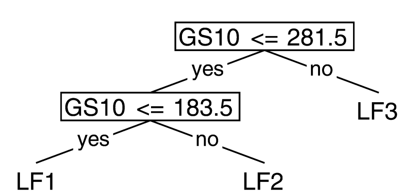
Linear functions LF1 to LF6 (Fig. 4) include the same variables: elevation (ELV), inclination (INC), phyto-geografical region (PHYTOREG), growing stock of the previous two periods (GS00 and GS90) and annual allowable cut for all time periods (E00, E90, E80 and E70). The structure of linear functions suggests that the strongest influence on the growing stock in the current period (GS10) is inflicted by the growing stocks of the previous two periods. The influence of the time dependent variables, which is reflected in the coefficients' values, decreases with the difference between the estimated period (i.e., 2010) and period to which they relate.

When compared to the above model for growing stock in state owned forests, the model for private owned forests (Fig. 5) consists just of the growing stock in the previous period. Root mean squared error of the model for private owned forests, estimated with 10-fold cross validation, is 55.07 m^3/ha. This is a bit worse than the model for the growing stock in state owned; therefore, the model for private owned forest is slightly less reliable than the model for state owned forest. The structure of linear functions LF1–LF3 (Fig. 5) is similar as in the case of state owned forest, with growing stock of the previous two periods (GS00 and GS90) being the two most important variables, followed by phyto-geographical region (PHYTOREG) and site productivity index (PI).

Next, we have to correct the above described models in order to obtain models for predicting the growing stock in year 2020. Basically, we keep the same structure of the models (trees and equations), but we change (shift for one decade) the time dependent variables and correct the constant terms in linear equations. The new values for the constant terms were obtained by linear extrapolations of the temporal growing stock trend of compartments falling under each linear equation (LF). The models constructed in this way are presented in Figs. 6 and 7.

The values of measured and modelled growing stock for private owned and state owned forests obtained by our models (Figs. 6 and 7) are presented in Tables 2 and 3. The growth rates of predicted growing stock in state owned (Table 2) and private owned (Table 3) forests expectedly show the largest increase in compartments with lower growing stock in 2010, while the smallest increase can be observed in compartments with the highest growing stock in 2010.

The trends of growing stock for private owned forests show larger increase than for state owned forests, and the difference between private owned and state owned forests is therefore getting smaller (Fig. 8). The predicted growing stock in 2020 in private owned forests is 327 m^3/ha and 343 m^3/ha in state owned forest. The average growing stock for the entire study area is 334 m^3/ha. The state owned forests had a higher growing stock throughout the studied period (from 1970 to 2020). However, from the plot (Fig. 8)



LF1: GS20 = -0.0387 * ELV + 0.0845 * PI=11,3,7,15,17 + 0.0795 * (PHYTOREG=Prealpine, Alpine) + 0.0001 * GS80 + 0.2302 * GS00 + 0.6201 * GS10 + 171.210
LF2: GS20 = 0 * ELV + 14.6206 * PI=11,3,7,15,17 + 15.1998 * (PHYTOREG=Prealpine, Alpine) + 0.0203 * GS80 + 0.2167 * GS00 + 0.3798 * GS10 + 153.859
LF3: GS20 = 0.0399 * ELV + 10.8066 * PI=11,3,7,15,17 + 0.0283 * (PHYTOREG=Prealpine, Alpine) + 0.0001 * GS80 + 0.1484 * GS00 + 0.591 * GS10 + 85.186

Fig. 7. Model of the growing stock in private forests for 2020.

Table 2
The measured and modelled growing stock for 2010 and predicted growing stock for 2020 in state owned forests.

	Forest compartments in					
	LF1	LF2	LF3	LF4	LF5	LF6
Measured growing stock for 2010[a] [m^3/ha]	148.5	198.0	217.1	251.6	296.2	392.1
Modelled growing stock for 2010 [m^3/ha]	148.4	197.3	217.0	251.7	296.4	392.0
Predicted growing stock for 2020 [m^3/ha]	224.9	316.4	282.7	351.3	361.8	423.6
Growth rate [%]	151	160	130	140	122	108

[a] Average growing stock in compartments classified in the leaf of the model tree model (Fig. 4).

Table 3
The measured and modelled growing stock for 2010 and predicted growing stock for 2020 in private forests.

	Forest compartments in		
	LF1	LF2	LF3
Measured growing stock for 2010[a] [m^3/ha]	224.4	280.0	351.7
Modelled growing stock for 2010 [m^3/ha]	224.5	279.6	351.7
Predicted growing stock for 2020 [m^3/ha]	319.3	338.1	370.1
Growth rate [%]	142	121	105

[a] Average growing stock in compartments classified in the leaf of the model tree model (Fig. 5).

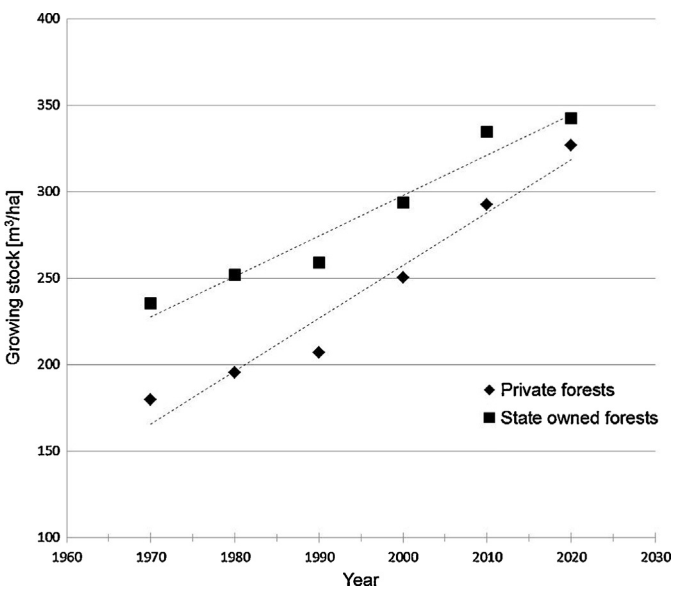


Fig. 8. Growing stock in private owned and state owned forests, including the predicted values for 2020.

we can see that the difference between the growing stock of private owned and state owned forests is decreasing since 1990.

4. Discussion

The time trends of growing stock are increasing in the entire studied period (1970–2010), while the accumulation of growing stock is much more intensive after the year 1990. Despite similar trends in accumulation of growing stock, the intensity of changes that affect accumulation trends are not the same for private owned and state owned forests. The most important variable in the private owned forests is the phyto-geographic region (an area with uniform climatic conditions that has a distinctly recognisable type of vegetation) followed by the site productivity and the altitude (Fig. 2), while the top-most indicator for state owned forests is the site productivity, followed by the altitude and the bedrock (Fig. 3). In all models, the annual allowable cut, as an indicator of forest management intensity, was surprisingly not included in the model structure. This could be explained by the fact that, in the past few decades, a nature-based forestry (Diaci, 2006) with a relatively low and to the site and stand conditions adapted allowable cut was applied through the intensive forest management planning in the entire study area. However, Diaci (2006) noticed that changes of forest management intensity may be aslo due to increasing importance of social functions, protection of extensive forest areas, decrease of subventions for forest tending, decrease of interest for regular forest management and price decrease of large diameter timber. These could be additional important reasons why the nature-based forestry might not be the only reason for those changes. If we investigate the absolute values of growing stock for individual trend types (leaves in the multi-target decision trees in Figs. 2 and 3), we notice that forests with low growing stock are located either in the areas with non-favourable conditions for forest growth (e.g., low site productivity index) or in lower altitudes, which were in the last centuries more exposed to human exploitation, due to their vicinity to more densely populated regions. As we can see, the multi-target models can provide us with explanations for different trends of the growing stock, however, they cannot be used for predicting the growing stock in the future.

Predictions of the growing stock in year 2020 are made with single-target model trees, where the growing stock at a specific time point is the dependent variable. The structure of model trees for the private owned forest consists of the growing stock in the previous decade (Fig. 5), while the model tree for the state owned forests contains also the annual allowable cut (Fig. 4). In model trees we also have to take into account the linear functions in the leaves, which describe influences of additional variables on the growing stock. Linear models for both forest groups consist of environmental variables describing quality of growing conditions (elevation, inclination, phyto-geographical region, site productivity), state of the growing stock in the previous periods and variables describing intensity of forest management (annual allowable cut) in the whole observed period (1970–2000). In both models the effects of time dependent variables decrease with time. The structures of model trees and their linear functions confirm that modelling the growing stock requires inclusion of many complex interactions between various variables, and not only the dendrometric characteristics of forest stands.

The average predicted growing stock for the entire study area, 334 m^3/ha in year 2020, is very close to the prediction given by the European Forest Sector Outlook Study II, 345 m^3/ha for year 2020 (EFSOS, 2011). Remarkably similar to the European Forest Sector Outlook Study II prediction is our prediction for state owned forest, which is 343 m^3/ha. Another high similarity is the growth rate of growing stock for a period 2010–2020, which is 1.044 in our models, and 1.045 in predictions of the European Forest Sector Outlook Study II. Despite similar results, our research provides many more descriptions and detailed explanations of the driving forces involved in the processes of growing stock accumulation, and it should be noted that our models use as an input far simpler data than the above mentioned study. The coefficients of extrapolated linear functions (k-values) expectedly show a much larger increase of growing stock in the forests with a lower current growing stock, while the linear extrapolated functions for forests with the highest current growing stock (Tables 2 and 3) show the smallest increase. This indicates that Slovenian forests are accumulating their growing stock very fast, which means that the production potential of forests is increasing, especially in the forests with a high proportion of young stand development phases.

From the predictive models (Fig. 8) we can also see that the difference between private owned and state owned forests is getting smaller. This could be explained with higher accumulation of growing stock in the private owned forests due to the reduction of exploitation intensity of private forests, which is reflected in lower utilization of prescribed available annual cut (Jonozovič et al., 2012) and in the decline of economic interest for forest exploitation. This trend stopped recently when the economic situation changed significantly due to the recession of modern economy and forests became again an important source of income for forest owners, which results in increasing utilization of prescribed cut (data not shown). Furthermore, the planned available annual cut in the period 2011–2020 increased due to the improved status of forest resources (Jonozovič et al., 2012). Both aspects will probably result in reduced accumulation of growing stock in the future, but they could not be included in our models, which are only based on the available historical data.

The results of our study are also very important in terms of development and use of indicators. Dale and Beyeler (2001) raise three main hampers to the use of ecological indicators as a resource management tools. The first limitation is the small number of indicators which are used to deal with complex ecological systems (e.g., forest). In our study, we used a set of 47 indicators and environmental variables to describe each of 21,052 forest compartments for a period from 1970 to 2010. Quality of data is provided with official methodology of forest inventory made by Slovenian Forestry Service (SFS, 2010; Kovač et al., 2009). However, this large set of indicators and environmental variables doesn't yet allow their application because they have to be first selected in order to measure characteristics that most closely relate to management concerns. This represents the second most common problem of the use of indicators posted by Dale and Beyeler (2001).

However, the selection of indicators is a very demanding task, which is usually addressed with the individual selection of indicators into a suite of indicators or by introducing multimetric (Hilsenhoff, 1982) or multivariate (Reynoldson et al., 1997; Karr, 2000) indexes. They synthesize a large number of indicators into a value of the specific index with limited or low explanatory power. In our case the selection of variables and indicators is performed by data mining algorithm according their information content. The selection in presented in a form of hierarchical structure of decision tree while its leaves contain linear equations with selected indicators for precise prediction of the focused indicator (e.g., growing stock). This methodological approach addresses also the third obstacle noted by Dale and Beyeler (2001), which is the interpretation of indicators which change their value through space and time. Our methodology was able to give reasonable explanations for temporal dynamics of growing stock through the study period. Even more, it classifies trends and describes hierarchical influences of indicators and variables on each class of growing stock trend. Our methodology also solves the problem of static set of indicators because the structure of a decision tree changes according to the changes of the system.

Due to the influence of stochastic processes, problems with the quality of data collected by national inventories and nondeterministic properties of ecological models, the predictions of growing stock can never be completely accurate. However, our results can be used as a part of a decision support system, where they would be combined with existing expert knowledge in order to provide the best possible support to the forest managers and forest policy.

5. Conclusions

Based on the presented results, we can conclude that data mining methods can extract useful and interesting models and knowledge from forest inventory databases, such as Silva-SI. The models we have developed describe the temporal dynamics of growing stock and predict the growing stock in the future. The induced models can be used to give reliable estimates for private owned and state owned forests. The models complement the classical mechanistic models and they give us a possibility to make also ex-ante predictions, which can provide us with practical and relevant information for forest management planning at the national level, as well as at the regional level and the level of forest ownership classes.

Two important conclusions can be exposed. First, the proposed modelling approach allows for the optimization of the model structure according to the characteristics of the data, thus allowing the identification of data clusters (represented by model tree leaves), and determination of the most influential indicators within each leaf and interactions between these indicators. Furthermore, the explanations for different trends of growing stock in Slovenian forests and the results of prediction models of growing stock for the period 2010 to 2020 are similar to outcome of scenario analysis of the European Forest Sector Outlook Study II (EFSOS, 2011), despite that used methodologies were different. Second, our models can be used as a complement to the classical mechanistic models, despite the fact that they are based only on the available inventory data. These conclusions show that methodological problems exposed by Dale and Beyeler (2001) about the use of indicators as a resource management tools could be solved by introduction of data mining methodology in investigations based on ecological indicators.

This promising methodological approach could be extended for the use by international and national organisations for analyses of the state of forests in particular (e.g., Montreal Process, Pan-European Process) and to wider areas of investigations based on ecological indicators in general.

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