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Drivers of forest harvesting intensity patterns in Europe

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ABSTRACT

Forests provide humankind with essential raw materials and the demand for these materials is increasing. Further expanding forestry into unmanaged forests is environmentally costly and increasing forest area via plantations will not immediately lead to increased wood supply. Thus, just like in agriculture, forestry faces the challenge how to intensify forest management in existing production forests in sustainable ways. Yet, our current understanding of what determines forest management intensity is weak, particularly at broad scales, and this makes it difficult to assess the environmental and social trade-offs of intensification. Here, we analyse spatial patterns of forest harvesting intensity as one indicator for forest management intensity across Europe, a region where most forests suitable for production are already in use and where future intensification is likely. To measure forest harvesting intensity, we related harvested timber volumes to net annual increment for the period 2000–2010. We used boosted regression trees to analyse the spatial determinants of forest harvesting intensity using a comprehensive set of biophysical and socioeconomic explanatory variables. Our results show that forest harvesting intensity varied markedly across Europe and harvested timber volumes were well below the increment in most regions. Harvesting intensity was especially high in southern Finland, southern Sweden, southwestern France, Switzerland, and the Czech Republic. The spatial patterns of forest harvesting intensity were well explained by forest-resource related variables (i.e., the share of plantation species, growing stock, forest cover), site conditions (i.e., topography, accessibility), and country-specific characteristics, whereas socioeconomic variables were less important. We also found the relationship between forest harvesting intensity and some of its predictors (e.g., share of plantation species, accessibility) to be strongly non-linear and characterised by thresholds. In summary, our study highlights candidate areas where potentials for sustainably intensifying timber production may exist. Our analyses of the spatial determinants of harvesting intensity also provides concrete starting points for developing measures targeted at increasing regional wood supply from forests or lowering harvest pressure in regions where forests are heavily used. Finally, our study emphasises the importance for systems' understanding for designing and implementing effective sustainable forest management policies.

1. Introduction

Land use provides humanity with essential food, fibre, and bioenergy, but is also a major force of global environmental change (MA, 2005; Haberl et al., 2007; Pereira et al., 2010). As fertile land is getting scarce (Lambin and Meyfroidt, 2011) and further expansion of land use into remaining wildlands incurs high environmental costs, future production increases will, to a large extent, have to rely on sustainably intensifying land already in use (Foley et al., 2011; Tilman et al., 2011). Yet, assessing where future production can be increased and understanding the trade-offs of intensification is currently limited by incomplete knowledge about the spatial patterns and drivers of intensification pathways, especially at broad geographic scales (Verburg et al., 2009; Erb, 2012; Lambin et al., 2001).

This is particularly the case in forestry, where the spatial patterns of forest management intensity and the drivers that produce these patterns remain highly unclear. This is unfortunate, because

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forest management effects on forest ecosystem functioning vary substantially depending on management intensity. For example, the intensity by which forests are managed affects forest structure (Vilén et al., 2012), soils (Jandl et al., 2007), biogeochemical cycles (Nabuurs et al., 2013; Luyssaert et al., 2012), biodiversity (Paillet et al., 2010), and ecosystem service provisioning (Gamfeldt et al., 2013). Understanding the spatial patterns of forest management intensity and its drivers is therefore important for assessing the environmental trade-offs of forestry and for identifying opportunities for sustainable intensification.

Assessing forest management intensity is challenging because intensity itself is a complex term, encompassing multiple dimensions (Schall and Ammer, 2013). Consequently, forest management intensity has been examined using a wide range of indicators, including harvested timber volumes, forest structural parameters (e.g., the difference between potential and actual biomass storage), stand establishment practices, tree species composition, length of rotation periods, human appropriated net primary production, or the amount of fertiliser, herbicides, and machinery used (Luyssaert et al., 2011; Forest Europe and UNECE FAO, 2011; Duncker et al., 2012). Intensity metrics, which relate inputs (e.g., capital), outputs (e.g., harvested timber volumes), or system properties (e.g., ecosystem productivity) to each other, can provide insights into land use intensity patterns and drivers (Erb et al., 2013; Kuemmerle et al., 2013). For example, interpreting harvested timber volumes without considering ecosystem productivity could be misleading as the same volume of timber extracted from forest systems with high or low productivity may indicate very different levels of forest harvesting intensity. By expressing harvested timber volumes in relation to the net annual increment, forest harvesting intensity can be assessed across large regions.

Unfortunately, studies assessing forest harvesting intensity have either focussed on the national scale (e.g., relying on national forest resource assessments, (Kuusela, 1994; Forest Europe and UNECE FAO, 2011), or on small study regions (see Schall and Ammer, 2013 for an overview), both of which precludes understanding spatial patterns of management intensity. Only two studies addressed drivers of forest harvesting patterns at broad spatial scales. Analysing timber harvesting patterns in European Russia showed that road density, forest composition, and total forest area were important determinants of harvesting patterns (Wendland et al., 2011). A range of spatial variables including tree species composition, slope, forest coverage, proximity to cities, and conservation areas allowed mapping different forest management systems in Europe using an expert-based approach (Hengeveld et al., 2012). We know of no study explicitly addressing broad-scale patterns of forest harvesting intensity.

Evidence on the drivers of forest owner's decisions to manage their forest intensely or not was only derived from local-scale case studies. These studies, mainly focussing on non-industrial, private forest owners, show that a range of policy, forest resource, and market factors are potentially important in determining timber volumes extracted (Beach et al., 2005; Amacher et al., 2003). For example, forest management plans, property size, and income from agriculture determined harvesting decisions in Norway (Størdal et al., 2008), ownership size and type shaped harvesting decisions in the southern US (Arano and Munn, 2006), or the demand for wood products and associated price changes were important drivers of harvesting decisions in the US and Australia (Adams et al., 1991; van Putten and Jennings, 2010). Furthermore, population density, forest size, and distance to urban areas influenced harvesting in the US (Wear et al., 1999; Munn et al., 2002). Yet, none of these studies addressed patterns and drivers of forest harvesting intensity for larger regions. Clearly, there is a research gap at the regional scale, which is unfortunate because of its major importance for policy making and for mitigating the impacts of global environmental change (Wu, 2013).

Regression models are powerful tools to assess drivers and determinants of land use patterns (Müller et al., 2011; Baumann et al., 2011; Wendland et al., 2011). Algorithmic models are particularly promising because they do not impose any a priori relationship between target and predictor variables. Fewer requirements on the data structure make them well-suited to investigate the complex and often non-linear interactions between predictors and response in land systems. Algorithmic models, such as boosted regression trees (BRT), generally attain a higher model fit and predictive accuracy than traditional statistical approaches (Elith et al., 2006; Lakes et al., 2009; Lin et al., 2011). Because of their higher predictive accuracy, better ability to generalise from data, and possibility to handle large heterogeneous data sets, algorithmic models are gaining growing attention in ecology (Leathwick et al., 2006; De'ath and Fabricius, 2000) and land change science (Müller et al., 2013; Gellrich et al., 2008), but no study has so far used BRTs to assess spatial determinants of forest harvesting intensity.

In this study, we sought to quantify and understand broad-scale spatial determinants of forest harvesting intensity patterns across the European Union (EU-27) plus Norway and Switzerland. As intensity metric, we used the ratio of harvested timber volume (fellings and harvest losses) and net annual increment volume (hereafter referred to as "forest harvesting intensity") because this ratio is an important criterion to assess the sustainability of forest resource use. As explanatory variables, we focused on selected factors that are indirect proxies of the underlying drivers of forest harvesting intensity (hereafter referred to as "spatial determinants").

Europe is an interesting case for assessing forestry intensity since forest use in Europe has a long history. After centuries of extensive deforestation, Europe's forests increased in the 19th and 20th century as a result of farmland abandonment, afforestation, and nature protection (Kaplan et al., 2012; Rudel et al., 2005), and forests now cover 37% of Europe's terrestrial surface. Though forest cover has increased steadily during the last decades (0.37% per year, Forest Europe and UNECE FAO, 2011), forest harvesting intensity also remarkably increased from 58% (1990) to 62.4% (2010) and is expected to increase further (UNECE and FAO, 2011; Böttcher et al., 2012). Forest cover is distributed very unevenly across Europe and the region is furthermore characterised by large environmental (e.g., boreal to Mediterranean), historical (e.g., capitalism vs. socialism), ethnic, and economic (highly industrialised vs. less industrialised economies) heterogeneity. How this heterogeneity relates to spatial patterns in forest harvesting intensity remains largely unclear. Understanding forest harvesting intensity is one key aspect for assessing forest management intensity. To ensure the sustainable intensification of forest management in light of growing demands for timber products would, however, require a range of indicators addressing the multidimensionality of forest management intensity.

We compiled time series of sub-national forest harvesting intensity patterns in Europe between 2000 and 2010 and used boosted regression trees to quantify the influence of a set of biophysical, infrastructure, and socioeconomic variables in shaping these patterns. Specifically, we ask the following research questions:

1. What are the spatial patterns of forest harvesting intensity in Europe?
2. What are the most influential spatial determinants of these patterns and what is their relative importance?
3. What is the nature of the relationships between forest harvesting intensity and its spatial determinants?

2. Material and methods

2.1. Data

2.1.1. Forest harvesting intensity

To estimate forest harvesting intensity, we collected sub-national forest harvesting statistics (m^3/ha), net annual increment (m^3/ha), and forest area (ha) from national forestry reports, statistical yearbooks and databases, and by contacting national experts. Statistics were collected for the entire EU-27 plus Norway and Switzerland and – when possible – for each year between 2000 and 2010 (see Tables A.1–A.3 for a full list of references). Data were collected for administrative units ranging from the national scale (for small countries) to the district level (for large countries), with 1 to 107 regions representing a single country (see in Section 3). We excluded six regions with major data gaps resulting in 454 administrative units that were used for subsequent analysis.

The dataset was harmonised to correct for differences in national harvesting definitions (e.g., harvesting volume over or under bark, in- or exclusion of harvest losses). To do so, we calculated the annual volume share per region in the total harvest volume for a particular country based on the regional statistics, and used those shares to subdivide national-level, harmonised harvest data representing roundwood removals (m^3) under bark and fuelwood (FAOSTAT, 2012). Data for some regions (see Table A.1) were missing for certain years and we then assumed an identical volume share of the national harvest levels for the closest years where data were available. The same data collection and harmonisation steps were repeated for statistics concerning net annual increment (NAI) and forest area (see Tables A.2 and A.3), which were harmonised with reported increment levels and forest area for the year 2000 (Forest Europe and UNECE FAO, 2011) to correct for differences in national harvesting definitions. To facilitate the comparison of forest harvest intensity across years, we used the average net annual increment for the period 2000–2010. To convert wood removals to fellings, we added bark (Forest Europe and UNECE FAO, 2011; UNECE and FAO, 2010) and stem harvest losses (UNECE and FAO, 2000). Based on these data, we calculated the volume of wood fellings and NAI and subsequently forest harvesting intensity (as a percentage) for the period 2000–2010.

2.1.2. Predictor variables

We reviewed studies investigating harvesting decisions to identify a set of variables potentially influencing forest harvesting intensity. The reviewed studies were mostly conducted on local to regional scale and we assumed that the influence of the identified variables on forest harvesting intensity found by these studies would potentially also apply at the pan-European scale. Due to the deductive and exploratory character of our study, we did not impose any ranking of a variables' influence, whereas the general type of relationship between variable and forest harvesting intensity was hypothesised a priori (Table 1; see Text A.1 for the rationale behind selecting the variables used in our analyses and detailed information on the sources of these variables). We identified 23 predictor variables that we hypothesise to potentially influence forest harvesting intensity in Europe. We grouped the predictor variables – except the country dummy – into three main groups: (i) forest resource variables, (ii) environmental conditions, and (iii) other socioeconomic variables. Thirteen variables were available as raster layers, the majority with a 1×1 km^2 native resolution. We re-projected all raster layers into the Lambert Azimuthal Equal Area projection and used bilinear interpolation to resample growing stock and ruggedness data from their native resolutions to the 1×1 km^2 target resolution. Subsequent to the harmonisation of predictors, we aggregated these variables to the administrative units of the target variable. Therefore, we weighted data related to non-forest land covers with a continuously scaled forest cover map to represent forested areas more prominent when calculating average values for the utilised administrative units. To do so, we used the forest map by Pekkarinen et al. (2009), which

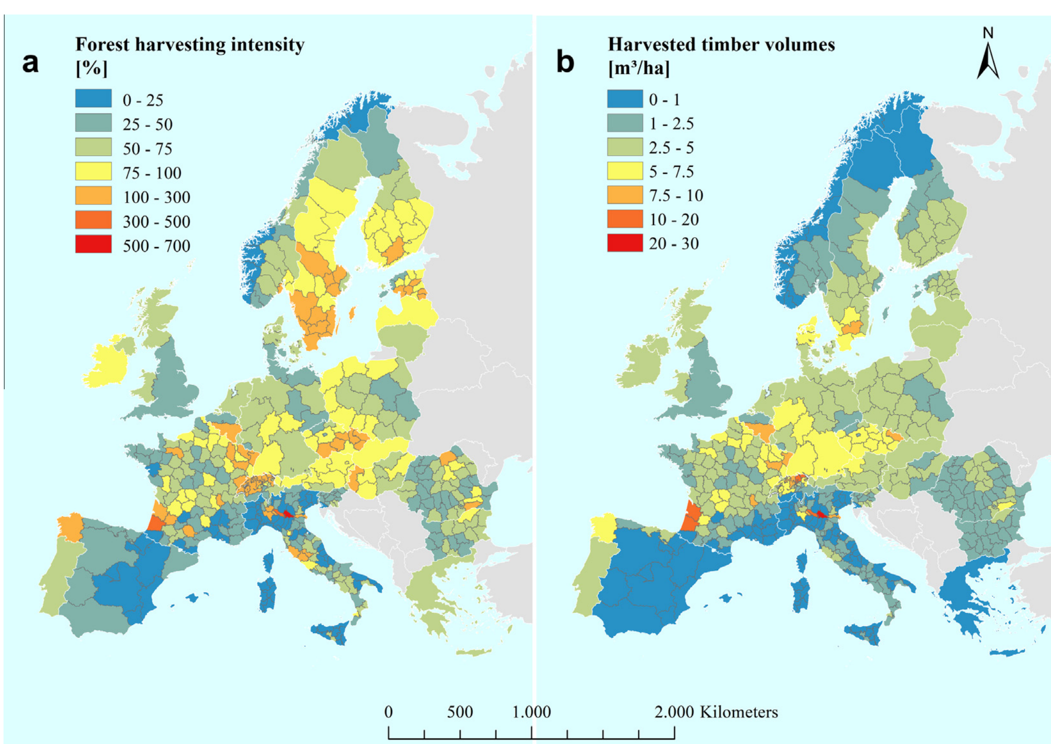

Fig. 1. European administrative units (NUTS0-3) showing (a) average forest harvesting intensity (%) and (b) average harvested timber volumes (m^3/ha) for 2000–2010.

Table 1
Description of single predictors, their measurement units, resolutions (*Res*), data sources, descriptive statistics, spearman correlations (*Corr*) and expected relations (*Sign*) with forest harvesting intensity, and data formats (*Format*). Descriptive statistics were calculated for numeric variables only. Symbols for *Sign* indicate whether predictor increases go along with increases (+) or decreases (–) in forest harvesting intensity or no explicit relationship (•). Abbreviations in the column *Format* are: R – raster, V – vector, S – static, and D – dynamic. Time-variant variables are marked with an asterisk and their descriptive statistics were calculated with averaged values.

Factor	Predictor name	Description	Unit	Res	Source	Mean	SD	Corr	Sign	Format
Forest resources	BEECHOAK	Share of beech (*Fagus spp.*) and oak (*Quercus spp.*) in total species	%	1 km	Brus et al. (2012)	22.34	18.63	−0.14	+	R,S
	FCOV	Forest cover of Europe	%	1 km	Pekkarinen et al. (2009) and Schuck et al. (2002)	34.55	18.72	0.14	+	R,S
	PINESPRUCE	Share of pine (*Pinus sylvestris*) and spruce (*Picea spp.*) in total species	%	1 km	Brus et al. (2012)	29.85	28.43	0.39	+	R,S
	PLANTATION	Share of plantation species (*Robinia spp., Populus spp., Eucalyptus spp., Pinus pinaster*) in total species	%	1 km	Brus et al. (2012)	6.55	10.04	−0.27	+	R,S
	TOTPROT	Share of protected forest in total forest	%	1 km	IUCN and UNEP-WCMC (2012) and EEA (2011)	19.13	18.95	−0.06	–	R,S
	TOTVOL	Total growing stock	m^3/ha	500 m	Gallaun et al. (2010)	154.15	70.40	0.31	+	R,S
Environmental conditions	POORSOIL	Share of low productive soil limiting growth	%	1 km	Driessen et al. (2001), EC (2006), Verkerk et al. (2011)	11.07	16.60	−0.16	–	R,S
	PRCP5M	Precipitation sums of growing season	mm	1 km	Hijmans et al. (2005)	330.42	106.61	0.01	+	R,S
	RUGG	Terrain ruggedness expressing relief energy	m	~1 km	NASA (2006) and Riley et al. (1999)	68.05	61.96	−0.43	–	R,S
	SBC	Share of soil types with no bearing capacity	%	1 km	EC (2006) and Verkerk et al. (2011)	7.95	13.84	0.24	–	R,S
	TEMP	Long term mean temperature	°C	1 km	Hijmans et al. (2005)	8.45	3.20	−0.33	+	R,S
	WATSHORT	Difference between precipitation potential evapo-transpiration, both during growing season	mm	1 km	New et al. (2002), Metzger et al. (2005) and Hijmans et al. (2005)	−27.22	38.95	0.14	–	R,S
	ACC50	Travel time to cities >50,000 inhab.	min	1 km	Nelson (2008)	137.37	84.60	−0.24	•	R,S
Socio-economy	FAOintens*	1 yr time lag of felling-to-increment ratios	%	•	See A.1–A.3	63.96	52.10	NA	+	V,D
	GDP PPS*	1 yr time lag of gross domestic product	%	•	EC (2012)	19,049	7938	−0.10	+	V,D
	GVAprim*	1 yr time lag of gross value added in I. sector	%	•	EC (2012)	457.15	948.29	0.08	+	V,D
	JOBLESS*	1 yr time lag of jobless ratios	%	•	EC (2012)	8.20	3.94	0.06	•	V,D
	LABOURprim*	1 yr time lag of labour force in I. sector	%	•	EC (2012)	32.89	62.38	0.02	+	V,D
	OIL*	1 yr time lag of heating oil prices incl. tax	%	•	EC (2013)	751.30	202.27	−0.18	+	V,D
	PRIVFOR	Share of privately owned forest	%	•	Pulla et al. (2013)	59.36	26.02	−0.11	+	V,S
	TIMBER*	1 yr time lag of timber prices	%	•	FAOSTAT (2012)	82.15	22.11	−0.40	+	V,D
	URBRUR	Urban–rural typology	–	•	EEA (2010)	NA	NA	NA	•	V,S
	COUNTRY	Dummy to capture country characteristics	–	•	Own calculation	NA	NA	NA	•	V,S

we calibrated to match regional-and national-level forest area statistics as described in Section 2.1.1 using the approach developed by Schuck et al. (2002). We then calculated the percentage change for one-, three-, and five-year periods for the socioeconomic variables that were available as annual time series on the utilised administrative units and merged them with the aggregated spatial data.

2.2. Boosted regression trees

We used boosted regression trees (BRTs) to quantify the influence of a set of spatial determinants in shaping forest harvesting intensity patterns in Europe. BRTs evolved in the tradition of machine learning techniques and belong to the family of non-parametric models. The most important difference to statistical approaches is that machine learning techniques are distribution-free (i.e., no a-prior assumptions on the distribution of the target variable or explanatory variables are made). Machine-learning techniques assume independent observations and that the process generating the data is complex and unknown, and therefore use an algorithm to learn the relationship between a target variable and explanatory variables (Breiman, 2001b; Elith et al., 2008). BRTs build upon decision trees, which explain the variance of a target variable by splitting up the variable space into rectangles in a binary fashion. A simple model (constant) is fitted to each partition by fitting the mean response for observations in that partition (Elith et al., 2008; Hastie et al., 2011). From the suite of available predictors, BRTs select those that minimise the prediction errors. This is the main difference to Random Forest models, where a random feature selection is applied before fitting individual trees (Breiman, 2001a). Contrary to decision trees with a single but potentially complex decision tree, BRTs use many simple decision trees in an ensemble (i.e., boosting). Boosting is a numerical optimisation technique that minimises the loss function of a model by adding trees in a forward stage-wise fashion (i.e., existing trees remain unchanged when more trees are added; only the fitted value is re-estimated). The first tree maximally reduces the loss function, whereas all following trees focus on the residuals of the previously fitted model, hence explicitly on the unexplained variance in the target variable (Elith et al., 2008). This leads to drastically increased predictive accuracy (Hastie et al., 2011; Friedman et al., 2000). BRTs do not tend to overfit because they introduce stochasticity by randomly withholding a certain percentage of the data while fitting the model (Dormann et al., 2013). Furthermore, BRTs are robust against missing data and collinearity of predictors while being able to handle non-linear relationships and interaction effects (Hastie et al., 2011; Elith et al., 2008). However, for interpreting the results, knowledge on the correlation structure between the predictors is beneficial which is depicted in Fig. A.2 in the Supplementary material. Interaction effects reinforce the shared influence of two predictors compared to decision trees with no variable interactions. Assessing the nature and magnitude of possible interaction effects yields a better understanding of the investigated phenomenon (Elith et al., 2008).

Generally, BRTs combine high predictive accuracy with good interpretability of results (Friedman, 2001), making them a preferable tool to investigate the spatial determinants of forest harvesting intensity. The calibration of BRTs necessitates specifying four main parameters: (i) number of trees (*nt*), (ii) tree complexity (*tc*), (iii) learning rate (*lr*), and (iv) bag fraction. The number of trees defines how many single decision trees are used in the model, tree complexity defines the maximum allowed interaction levels between predictors, the learning rate scales the contribution of each single decision tree to the entire BRT model, and the bag fraction defines the share of data that is withheld from the training data while fitting each single decision tree. A detailed mathematical introduction to BRTs is provided by Hastie et al. (2011) and a hands-on tutorial by Elith et al. (2008).

To explain the spatial determinants of forest harvesting intensity patterns, we carried out two analyses: First, we fitted a static model using the average forest harvesting intensity over the study period (2000–2010) as response and all static variables and averages of time-variant predictor variables as predictors. This model allows for the assessment the general spatial determinants of forest harvesting intensity patterns across Europe. Second, we fitted ten annual models, one for each year, using the annual time series of the target variable (from 2001 to 2010) as response and all static variables, change ratios of time-variant predictor variables, as well as the time lags of the target variable as predictors. Change ratios and time lags were tested for one-, three-, and five-year time periods separately. These time-variant models expand the static approach by insights into changes in the relative importance of predictor variables over time. Combining the model results yields a comprehensive understanding of static and time-variant spatial determinants of forest harvesting intensity in Europe.

We used the *dismo* package (Hijmans et al., 2013) in R (R Development Core Team, 2012) to perform all analyses. Different parameter settings might influence model performance and we therefore conducted a systematic sensitivity analysis to test all combinations of interaction levels from 1 to 9 and learning rates from 0.1 to 0.001 to identify optimal parameter settings for subsequent analyses by using 10-fold cross-validated correlation coefficients. To avoid stochastic bias, we calculated row and column averages and selected the parameter combination with the highest values for *tc* and *lr* (Table A.4). Lower learning rates were also tested but revealed model impairments and drastically increased computation time (results not shown). As a result of the sensitivity analysis, we chose an interaction level of 4 and a learning rate of 0.0025. For each model iteration we randomly withheld 50% of the full data set (without replacement) to fit the model. The number of trees was automatically determined by using the *gbm.step* routine provided by the *dismo* package. We did not exclude extreme values of forest harvesting intensity since BRTs are insensitive to outliers (Elith et al., 2008). Only variables with a relative contribution above that expected by chance (100%/number of variables; static: 100%/22 = 4.55%, dynamic: 100%/23 = 4.35%) were interpreted (Müller et al., 2013). We used partial dependency plots (PDPs) to investigate the relationship between each predictor and the target variable. PDPs depict a variable's influence along its data range while holding all other variables at their mean (Friedman, 2001). To enhance interpretability, all plots were smoothed using a spline interpolation except for categorical variables. To compare variable rankings for the time-variant model we calculated Kendall's *tau* (Kendall, 1938). We used the Moran's I measure of spatial autocorrelation (Moran, 1950) to investigate spatial clustering of forest harvesting intensity and model residuals. Moran's I values range from −1 (negative autocorrelation; dissimilar objects tend to cluster) to 1 (positive spatial autocorrelation; similar objects tend to cluster).

3. Results and interpretation

3.1. Patterns of forest harvesting intensity

The spatial patterns of average harvested timber volumes on the one hand, and our forest harvesting intensity index on the other hand differed substantially (Fig. 1). For example, southern Germany had generally high harvested volume levels (i.e., harvested timber volume per hectare forest), but relatively low forest harvesting intensity due to high forest productivity, whereas in southern Finland high forest harvesting intensity occurred despite lower harvest levels. Generally, harvested timber volumes are correlated with the productivity of forests, which is, to a large extent, explained by environmental conditions. Hence, patterns in harvested timber volumes do not linearly translate into forest harvesting intensity, highlighting the potential usefulness of our intensity measure.

Forest harvesting intensity also varied markedly across Europe (Fig. 1a) and showed moderate spatial clustering (static: Moran's $I = 0.342$; time-variant: avg. Moran's $I = 0.321$, $SD = 0.063$), i.e. that high forest harvesting intensity in one place is associated with high forest harvesting intensity in neighbouring spatial units. Generally, an increase in forest harvesting intensity was observable for Central Europe during the study period, whereas the intensity level of Scandinavian and Mediterranean countries remained largely constant (Fig. A.1). Averaged over the period 2000–2010, regions with high forest harvesting intensity occurred in the southern parts of Finland, Sweden, Estonia, Czech Republic, as well as in Switzerland and smaller areas of northwest Spain, southwest and eastern France, and some scattered regions in Italy. Harvested timber volumes exceeded increment volumes substantially in some of these regions, for example, in southern Sweden and southwest France. Both, southern Sweden and the southwest of France suffered from severe storm events in the study period. Hence, subsequent salvage logging could explain high forest harvesting intensity.

3.2. Model performance

The static BRT model explained 55% of the variation in forest harvesting intensity patterns, the time-variant models yielded on average an explanatory power of 42% ($SD = 5.02\%$), as all time-variant models had a lower performance than the static model (Table 2). Interestingly, incorporating time-variant predictors did not substantially improve model performances. Reasons for this might be time lags larger than the study period or the lack in quality of the utilised socioeconomic factors such as timber prices. Another reason might be the fact that, due to long rotation length, forest harvesting intensity generally does not strongly depend on annual changes but rather on static environmental and socioeconomic conditions. We observed an exceptionally low model performance in 2006 being more than two standard deviations lower than the average over the study period. A possible explanation might be that the storm Gudrun in 2005 significantly disturbed forest management schemes. Heavy salvage logging could have led to large timber stocks, which made forest harvesting unnecessary in the subsequent year. Fig. A.1 supports this assumption showing that almost entire Sweden showed higher forest harvesting intensity in 2005 compared to the previous years, followed by a drastic drop in 2006. Adaptations of forest management schemes along with negative trends in local roundwood prices as a consequence of destructive storms (Gardiner et al., 2010) may not be captured by the data and could have resulted in lower model performance in the year 2006. Model residuals did not reveal any distinct patterns of spatial autocorrelation (static: Moran's $I = 0.044$; dynamic:

Table 2
Training and validation performance for all models.

Model summary	Year										
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Static
Number of trees	5430	2870	2490	2850	2530	5440	1830	5560	4440	3750	6110
CV r	0.68	0.63	0.66	0.64	0.64	0.54	0.64	0.66	0.66	0.70	0.74
CV r^2	0.46	0.40	0.44	0.42	0.41	0.29	0.41	0.44	0.44	0.49	0.55
Train r	0.90	0.85	0.85	0.87	0.86	0.91	0.78	0.93	0.90	0.90	0.93
Train r^2	0.81	0.72	0.72	0.76	0.74	0.83	0.61	0.86	0.81	0.81	0.86
Mean total dev.	3415.98	2936.40	2280.80	2360.56	2897.20	7836.64	2688.18	3220.09	3512.75	3057.72	2708.38
Mean residual dev.	721.54	938.51	689.46	651.42	860.99	2034.04	1137.88	521.92	752.38	656.74	446.90
CV std. error	0.04	0.04	0.03	0.02	0.05	0.09	0.04	0.05	0.06	0.04	0.03
Est. cv deviance	1937.26	1857.76	1338.90	1486.88	1975.15	5764.77	1828.26	1654.21	1851.32	1589.78	1305.29
Est. cv deviance std error	641.73	656.38	248.65	421.09	741.20	2354.13	710.73	351.62	518.81	398.51	491.81

avg. Moran's $I = 0.056$, $SD = 0.031$) indicating good model specification and agreement with the independent error assumption (Crase et al., 2012).

3.3. Variable importance in the static model

The results of the static BRT model showed that the share of plantation species, terrain ruggedness, and country-specific characteristics contribute together to more than half of the model's explained variance (Fig. 2, see Table A.5). Additional forest-related variables (growing stock, forest cover, share of pines and spruces) and accessibility also contributed considerably while most socio-economic variables exerted little effect on forest harvesting intensity except for jobless ratio. Country-specific characteristics were important and suggest that much of the remaining unexplained variance were due to country-level variations not captured by the data. Environmental conditions such as temperature, precipitation, or soil quality, did not influence forest harvesting intensity significantly, possibly because our harvesting intensity index already controlled for a large share of productivity effects which are important determinants of ecosystem productivity and thus increment.

Fig. 3 displays the PDPs of all predictors selected for interpretation (see Section 2.2). The share of plantation species was the most important variable for explaining forest harvesting intensity. After an initial decline in predicted forest harvesting intensity, intensity drastically increases beyond a threshold of 20% plantation species cover and saturates beyond 40% at an intensity of 100–140%. This indicates that all regions with plantation cover beyond this critical value were predicted to be intensively harvested, whereas regions with plantation forest below the threshold were all managed at relatively lower intensity. A possible explanation for the initial decrease could be that plantation species occur either in sparsely forested areas or only infrequently in unmanaged forests consisting of different, non-industrial tree species. In both cases, harvesting of plantation species is unlikely. Scrutinising the spatial patterns of forest harvesting intensity and plantation species cover clearly reveals that intensive monoculture plantations constitute an important anthropogenic modification of forest ecosystems (Hartley, 2002) and that such intensively managed forests are concentrated in a few regions in Europe (e.g., in the Mediterranean countries, western France, and Romania, Fig. 4a). Plantation species, which are typically managed with short rotation cycles (see Text A.1 in the Supplementary material), are logically related to high forest harvesting intensity, as their occurrence is often caused by silvicultural measures with the intention of timber or biomass production. Interestingly, these areas are often not intensely managed with regard to our forest harvesting intensity measure, except for a few areas in western France and northern Italy. In contrast, high forest harvesting intensity occurred in Central and Eastern Europe, Scandinavia, and the Baltic countries where plantation coverage is low.

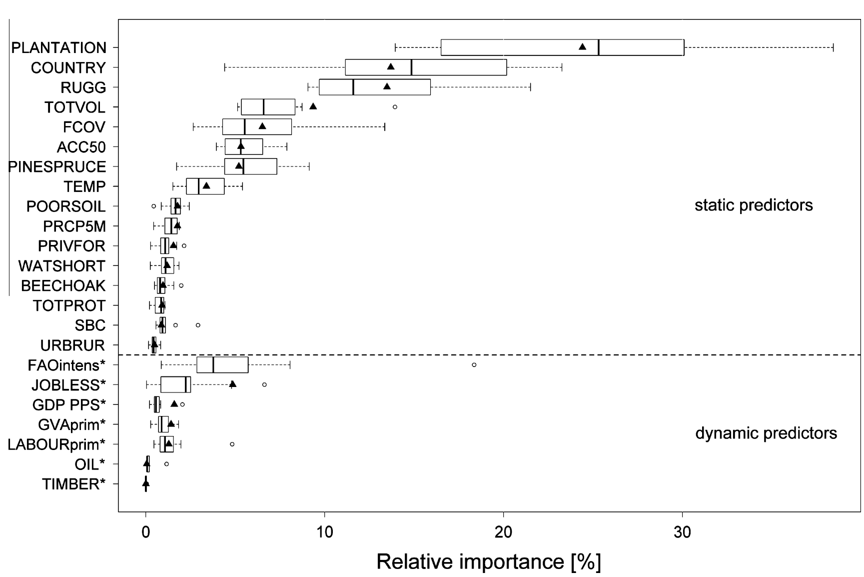

Fig. 2. Relative importance of predictors for the static (solid triangles) and time-variant (boxplots) model. Time-variant variables are marked with an asterisk and were averaged in the static model. In the time-variant model, one-year change ratios of the respective variables were used. Please refer to Table 1 for explanations of the variables.

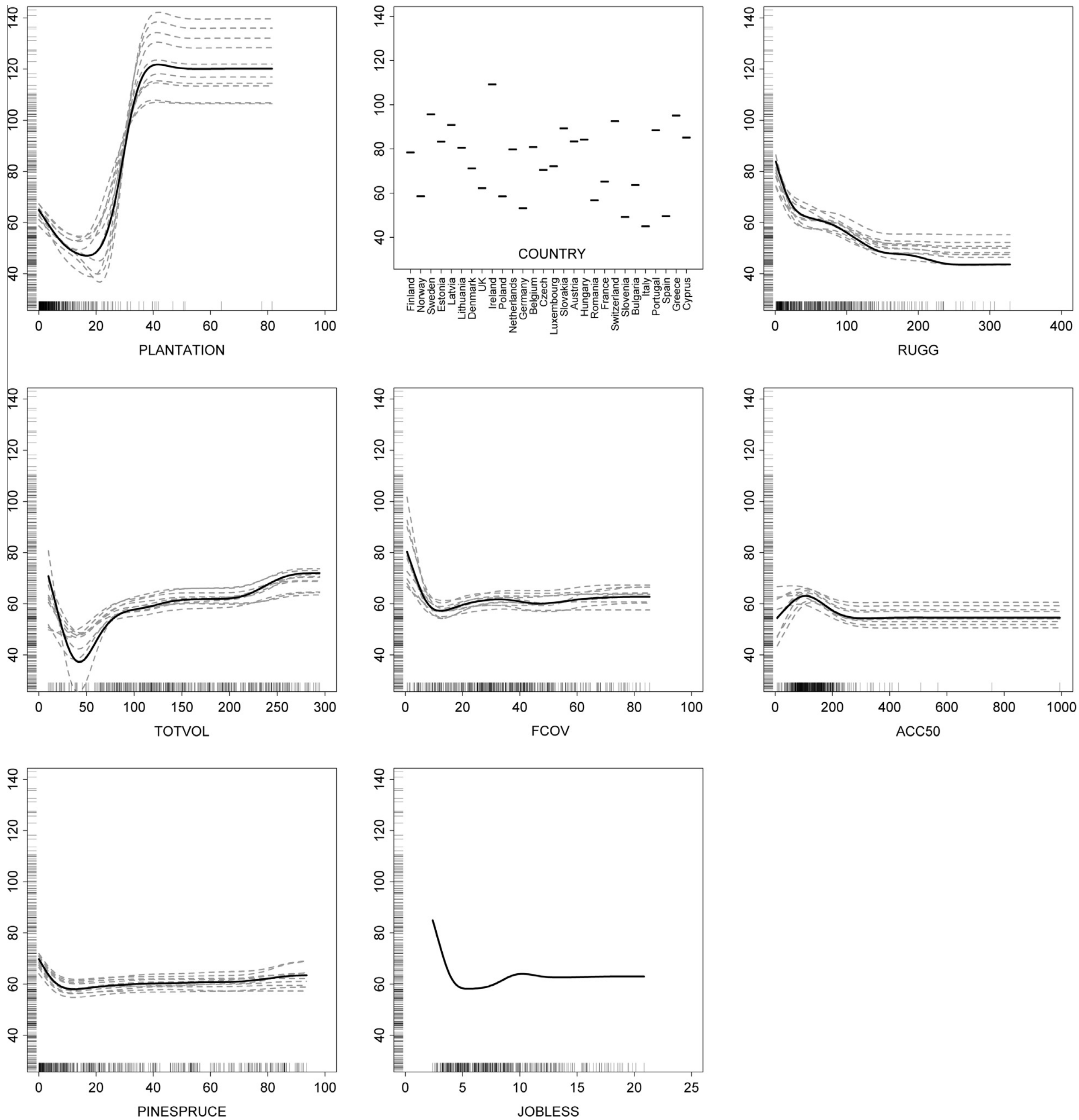

Fig. 3. Partial dependency plots (PDPs) for the eight most influential variables. The black, bold line represents the results from the static model, the dashed, grey lines the results for each year of the time-variant model. The vertical axis of the PDPs shows fitted values for each observation along the variable's data range displayed on the horizontal axis. Both axes are equipped with rug plots that visualise the distribution of the respective data space in percentiles. For JOBLESS*, only the average value is displayed since change ratios were used in the time-variant model resulting in a disagreement of units.

The second-most important variable in our model were country-specific differences in policies and socio-economics, captured by the country dummy. The influence of country-specific characteristics varies from predicted forest harvesting intensity of 40% in Italy to almost 120% in Ireland. High values of predicted forest harvesting intensity suggest that other predictors did not capture country-specific information. For example, in Ireland, Sitka spruce (*Picea sitchensis*) is an important forestry species (Department of Agriculture Food & the Marine, s.a.). However, the tree species map (Brus et al., 2012) does not distinguish between different spruce species (*Picea spp.*). Generally, country specific characteristics can capture differences in forest legislations and policies, traditions in forestry, differences in forest ownership structure, forest definitions, or fire and storm events, which all strongly shape forest harvesting intensity but could not be explicitly derived as explanatory variables.

Terrain ruggedness was the third-most important variable and forest harvesting intensity decreased with increasing ruggedness. Forest harvesting intensity was only half for regions with high relief energy, particularly for regions exceeding a ruggedness of 20 m. Strong ruggedness arguably limits forest harvesting intensity because costs of timber extraction increase (Simões and Fenner, 2010; Hengeveld et al., 2012). The fourth-most important variable was the total volume of growing stock and forest harvesting intensity increased with increasing biomass availability (Hengeveld et al., 2012). However, regions with less than 50 m^3/ha show

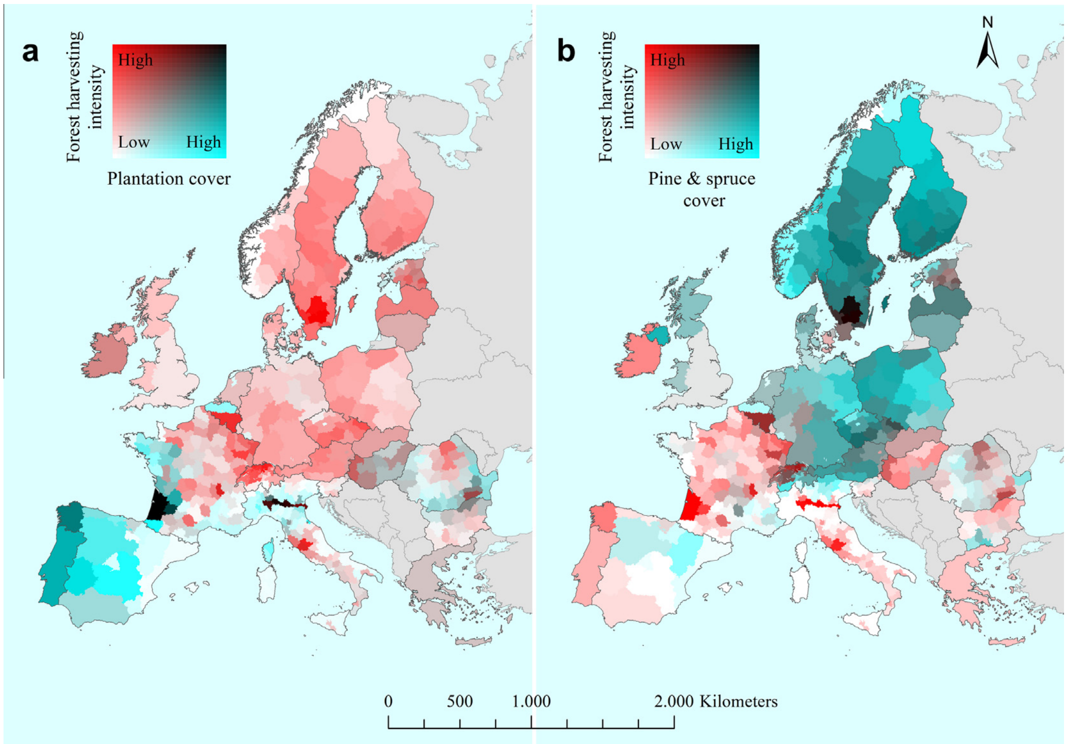

Fig. 4. Overlay map of forest harvesting intensity and plantation cover (a) and pine and spruce cover (b). All three variables were *z*-transformed for comparability. Bright blue colours indicate high tree species (plantation, pine and spruce) coverage, bright red colours indicate high forest harvesting intensity, white indicates low values for both plot variables, and black indicates high values for both plot variables. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

decreasing forest harvesting intensity with increasing growing stock volume, which may be due to low productivity or low or fragmented forest cover.

Forest cover was the fifth-most important variable and low forest cover co-occurred with lower predicted forest harvesting intensity. The explanation for this is straightforward since intensive harvesting can be done most efficiently in large forest patches (Hengeveld et al., 2012). The sixth-most important variable was accessibility. Our results showed an initial increase of forest harvesting intensity with increasing travel time to cities until it peaked at a travel distance of 60–90 min. Beyond this point, harvesting intensity decreased and finally levelled off at a distance of approximately 240 min. A reason for this hump-shaped relationship between accessibility and forest harvesting intensity could be that forests close to urban areas may have other functions (e.g., recreation), which could reduce logging activities in these areas (van Berkel and Verburg, 2011), thus providing support for the importance of urban-hinterland teleconnections (Seto et al., 2012). Another reason might be the negative impacts of transport systems. Large forest industry facilities require many transport movements, which are not wanted in or close to urban areas. Furthermore, a shortage of resources (more agricutlural areas in the vicinity of cities) and environmental impacts (e.g., odours from pulp and paper mills) may prevent high intensive use of forests near urban areas.

Long-rotation coniferous species (rank 7) and jobless ratio (rank 8) contributed only marginally to explaining forest harvesting intensity patterns. Forest harvesting intensity is almost stable along the data range of coniferous tree species cover with predicted values around 60%. This well reflects the approximate average forest harvesting intensity across Europe (see Section 1) and high pine and spruce cover goes along with medium to high forest harvesting intensity (e.g., in Central Europe, Scandinavia, and the Baltic countries, Fig. 4b). However, it has to be considered that our differentiation between plantation species and pine and spruce bases on rotation length. Pine and spruce can be interpreted as plantation species as well since they replaced broadleaved forests as Europe's natural forest type due to afforestation practices in the past (Bengtsson et al., 2000). With increasing jobless ratio, a slight increase in predicted forest harvesting intensity was observable with a peak around 10%.

3.4. Variable importance in the time-variant models

We used one-year change ratios and time lags for the time-variant models. Increasing the temporal delay reduced our time series due to data constraints and – when applied – did not improve model results (results not shown). Relative importance of predictor variables and their ranking in the time-variant models were in close agreement to the static model results described in Section 3.3 (see also Table A.5). Variable rankings were also quite constant over time with an average Kendall *tau* of 0.758 between years ($SD = 0.068$). Even though the overall model fit did not improve with the consideration of time-variant variables, augmenting the static model with temporal information was essential to investigate effects of socio-economic and natural events on forest harvesting intensity.

Time-lagged forest harvesting intensity (FAOintens*) was significant and fairly stationary over time, likely because transportation networks as well as wood-processing facilities are also relatively static over longer time periods. Hence, forest harvesting intensity in a particular year is a meaningful predictor of forest harvesting intensity in the subsequent year (see Fig. 2). Furthermore, unemployment ratios were important in the beginning of the study period (2000–2002) but showed only marginal influence in the end of the study period (2008–2010). The decrease in relative importance towards the end of the study period could be due to the economic situation deteriorating after the financial crisis in 2008 in many regions.

Most of the variables varied most strongly in and around the year 2006. Static variables dropped in importance whereas some socioeconomic variables drastically gained importance. For example, the influence of the time-lagged forest harvesting intensity peaked in 2006 with a relative contribution of almost 20% (other years: 0.86–8.06%) and thus outperforming all other predictors (Table 3). Furthermore, regional changes in the primary sector labour force were important in 2006 to explain forest harvesting intensity. This is not surprising considering the need for labour to clear the wind throws of the previous year. As stated in Section 3.2, the exceptionally low model performance in 2006 (see Table 2) could be caused by storm Gudrun in 2005 with subsequent salvage logging providing a more than adequate amount of timber, which can be the reason for strongly decreasing forest harvesting intensity in 2006. In fact, 2006 is the only year in our time series, which shows a strong deviation from the general forest harvesting intensity patterns (see Fig. A.1). Hence, only the time-lagged forest harvesting intensity could – to some degree – capture this exceptional behaviour. However, it has to be considered that other major storm events occurred during or shortly before the study period, e.g., Lothar in 1999, Kyrill in 2007, and Klaus in 2009, which all appear to not have exceptionally influenced forest management schemes and related forest harvesting intensity.

Both, the static and time-variant approach revealed that the four most important spatial determinants of forest harvesting intensity (share of plantation species, country-specific characteristics, terrain ruggedness, and growing stock) also occurred most often as interaction partners (Table A.6). Generally, time-variant predictors were only important in certain years, except the jobless ratio and time-lagged forest harvesting intensity. We detected strong interactions between plantation species cover and country-specific characteristics as well as terrain ruggedness.

4. Discussion and conclusion

Although the importance of forest management intensity to address sustained yield has been recognised long ago (von Carlowitz, 1713), quantitative, broad-scale assessments of the drivers and spatial patterns of forest management intensity have been missing. Here, we derived forest harvesting intensity patterns as one indicator for forest management intensity for all of Europe using, a system metrics relating the outputs from forestry (i.e., harvests) to ecosystem productivity (i.e., net increment). This allowed us to make forest harvesting intensity comparable across large regions characterised by strong environmental gradients and subsequently to quantify the most important spatial determinants of harvesting intensity at sub-national level. The main conclusions from our analyses and results were:

1. Forest harvesting intensity is distributed unevenly across Europe and harvested timber volumes were mostly well below the increment, thus indicating the potential for sustainable intensification in timber yields.
2. Forest harvesting intensity was well explained by forest-resource related variables (i.e., share of plantation species, growing stock), topography (i.e., terrain ruggedness), and country-specific characteristics.
3. Forest harvesting intensity and some of its predictors exhibit strongly non-linear relationships, sometimes characterised by thresholds. Identifying and understanding such relationships is important for designing and implementing effective sustainable forest management policies.

The spatial patterns of forest harvesting intensity showed marked differences, likely due to regional management practices. The hotspots of high forest harvesting intensity that we identified were mainly within traditional wood producing countries or regions such as Sweden, Finland, or southwest France. By using an intensity measure instead of harvested timber volumes alone,

Table 3
Relative importance of single predictors for the static and time-variant models. Data was missing for GDP PPS*, GVAprim*, and LABOURprim* for 2010. FAOintens* could not be incorporated in the static model since it does not have an average over the study period.

Predictors	Year										
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Static
Static											
PLANTATION	28.87	26.35	16.87	16.51	14.98	13.94	24.28	30.09	38.43	34.96	24.41
COUNTRY	12.17	14.47	20.54	15.24	20.17	4.40	23.26	11.16	9.29	15.66	13.69
RUGG	15.91	21.50	19.00	12.61	9.12	14.56	9.06	10.59	9.70	10.04	13.48
TOTVOL	5.13	5.34	8.34	7.15	5.88	13.93	6.48	8.73	6.69	5.19	9.35
FCOV	4.31	4.30	5.95	10.42	6.61	13.36	5.10	8.15	4.05	2.65	6.51
ACC50	4.32	4.43	6.34	7.88	6.53	3.94	4.73	7.74	4.66	5.88	5.31
PINESPRUCE	5.69	4.71	4.06	4.41	5.22	1.72	6.44	7.33	9.14	7.56	5.20
TEMP	2.30	1.51	2.27	5.41	4.29	2.93	1.72	2.98	4.39	4.56	3.39
POORSOIL	2.00	1.59	1.73	1.94	1.41	0.44	2.43	1.49	0.86	1.85	1.77
PRCP5M	1.32	1.78	1.75	1.87	1.54	0.44	1.12	1.06	1.02	1.61	1.77
PRIVFOR	2.14	1.28	1.26	1.09	0.83	0.27	0.94	0.81	1.06	1.72	1.54
WATSHORT	0.91	1.15	1.85	1.56	1.32	0.25	0.62	1.07	0.87	1.63	1.19
BEECHOAK	0.66	0.64	1.06	1.56	1.97	0.49	0.73	0.87	0.61	1.05	0.96
TOTPROT	0.85	1.00	1.00	1.07	0.85	0.21	0.52	0.90	0.50	0.61	0.90
SBC	1.00	0.79	0.67	1.10	1.66	2.91	1.00	0.86	0.57	0.81	0.87
URBRUR	0.57	0.51	0.59	0.83	0.43	0.15	0.29	0.35	0.40	0.43	0.48
Dynamic											
FAOintens*	2.86	0.86	2.59	3.96	8.06	18.35	5.72	3.23	4.30	3.58	NA
JOBLESS*	6.63	4.79	1.27	2.34	2.12	2.34	2.50	0.76	0.84	0.04	4.86
GDP PPS*	0.75	0.72	0.56	0.49	2.04	0.21	0.83	0.48	0.31	NA	1.59
GVAprim*	0.58	1.26	0.71	0.88	1.83	0.27	1.06	0.79	1.79	NA	1.41
LABOURprim*	0.80	0.96	1.54	1.48	1.96	4.83	1.07	0.52	0.45	NA	1.28
OIL*	0.19	0.05	0.05	0.19	1.16	0.06	0.08	0.04	0.07	0.15	0.05
TIMBER*	0.05	0.01	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.02	0.00

we avoided potential bias in assessing forest harvesting intensity by controlling for differences induced by forest productivity. Our study clearly shows the strong differences that exist between spatial patterns of harvested timber volumes and forest harvesting intensity, emphasising that assessing timber volume alone may only reveal limited information on management intensity. Despite being a quite simple index, forest harvesting intensity is one of the key indicators to assess sustainable forest management at the European scale. However, to address forest management intensity in an integrated way, further information on harvest frequency, size of production units, tree species selection, harvesting systems, or intensity and frequency of thinning and tending (Schall and Ammer, 2013) would have been useful but were not available due to the lack of data.

Generally, we found harvested timber volumes in Europe's forests to be substantially lower than the net annual increment (Europe-wide approximately 60–65%), resulting in increasing forest growing stocks (Ciais et al., 2008; Forest Europe and UNECE FAO, 2011). Aiming for sustainable use of forest resources, forest harvesting should not get close to or even exceed the annual increment of forests in the long run. Hence, results suggest, that many regions may thus have the capacity for future intensification of timber extraction without compromising the long-term sustainability in terms of wood yield. We caution though that a systemic view and a wide range of indicators should be considered to judge about the overall sustainability of forest management, including the consideration of biodiversity, biogeochemical, and social indicators. Moreover, even intensification at levels well below increment can have strong negative environmental outcomes. Our analyses also highlighted a few regions where harvested timber volumes exceeded the annual increment, which is in line with recent findings of the weakening forest carbon sink strength in Europe, partly because of increasing management intensity (Nabuurs et al., 2013). Harvested timber volumes above the increment can indicate the exploitation of old forests with slower growth rates or a lack of proper management in previous years resulting in short term exceedances. Such trends would, if continued over longer time periods, indicate unsustainable forest use. It is noteworthy to mention that at the national level, harvested timber volumes did not exceed the increment in any of the EU27 countries in 2010 (Forest Europe and UNECE FAO, 2011), whereas our results provide a more nuanced picture pinpointing intensely harvested regions.

Our analyses suggest that the share of plantation species, country-specific characteristics, terrain ruggedness, and growing stock were the most important spatial determinants of forest harvesting intensity. Both regression models we used revealed similar rankings of these predictors hence indicating the stability of our models. Static determinants were generally more important than time-variant ones. A possible explanation for this is that forest harvesting intensity generally depends on long-term environmental and socioeconomic conditions rather than year-to-year changes in such factors given relatively long rotation lengths in forestry. Further reasons could be that much of the information of time-variant socioeconomic variables has been absorbed by country specific characteristics as well as the lower data quality of time-variant predictors. For example, we did not have access to regional-level, annual timber prices and used an approximation using national-level price information on imported and exported roundwood. This is especially unfortunate since timber prices were expected to be an important driver of forest harvesting intensity (Beach et al., 2005). Hence, we assume that the coarse resolution and rough estimation of timber prices may mask their actual importance on forest harvesting intensity.

The identified spatial determinants of forest harvesting intensity differed in several aspects from prior, mainly fine-scale studies investigating the drivers of harvested timber volumes. Prior studies mainly found productivity-related variables to be important (e.g., Beach et al., 2005). An initial analysis revealed that productivity (i.e., net annual increment) was also the most important variable for explaining harvested timber volumes in our study region and model performance of analysing harvested volumes was even higher compared to analysing timber harvesting intensity (results not shown). However, using productivity as a predictor neither allows for assessing forest harvesting intensity, nor for identifying important influential drivers of harvesting which remain masked when not controlling for forest productivity. This again underlines the importance of using intensity metrics that consider system properties to analyse forest harvesting intensity. Comparing our intensity map with the only prior, yet qualitative assessment of forest management intensity on subnational level in Europe (Hengeveld et al., 2012) suggest overall good agreement between these maps. For example, both analyses highlight intensive areas especially in southern Sweden, southern Finland, and southwest France. Whereas the expert-based approach is static, susceptible to personal judgement in the selection of factors, and maps only potential forest management intensity, our approach incorporates time-variant information, identifies the most influential predictors, and addresses forest harvesting intensity explicitly.

A major finding from our study was that the relationship between forest harvesting intensity and predictor variables was sometimes highly non-linear and characterised by threshold-type responses. Such nonlinearity is characteristic for complex socio-ecological systems (Scheffer et al., 2012; Dearing et al., 2010) and emphasise the value of non-parametric statistical approaches. These tools can better uncover and visualise such relationships compared to traditional linear regression models, which have commonly been used. Here, we show that such thresholds may also exist for forestry systems at broad scales (e.g., for plantation species cover and accessibility in our case, Fig. 3). Because non-linearity in socio-ecological systems can result in surprising and sometimes irreversible outcomes, identifying and understanding non-linearity is important for sustainable resource management (Folke, 2006).

Our boosted regression tree models explained the variation of forest harvesting intensity well (up to 55% of the with-held variation) and resulted in plausible response curves and robust models without indication of overfitting. The explanatory power of our models was also substantially higher than in previous studies. Nevertheless, a few factors may explain remaining uncertainty. First, data constraints arguably prevented an even higher explanatory power of our models. For example, no data to capture the diversity of decision-making actors (national management plans, NGOs, nature protection organisations, companies, individuals) were available to us, although this should partly be captured by the country dummy. Furthermore, property size, despite being identified as an important determinant of harvesting on the local scale, could not be incorporated because such data are not readily available at the pan-European scale. The distance to wood processing units, such as pulp or saw mills, from harvesting sites likely influences forest harvesting intensity as it affects the procurement costs. Unfortunately, freely available, consistent, complete, and spatially-explicit datasets of processing unit locations are currently not available for all of Europe. It is noteworthy, that our market accessibility variable would likely be highly correlated with a processing unit accessibility variable. Duncker et al. (2012) suggest twelve major factors to characterise forest management intensity, yet not all of these factors could be represented in our dataset (e.g., we had no spatially explicit data on application of fertiliser or pesticides, machinery, or soil cultivation). Furthermore, rapid changes in forest management in response to storm events were only incorporated via our time-lagged forest harvesting intensity, and spatially explicit data on wind throws would have further improved our models. Second, some uncertainty remains due to different national forest harvesting reporting schemes, which may have led to bias in the target variable, even though we controlled for these differences by harmonising the data (see Section 2.1.1). Third, issues of scale cannot be ruled out for regions with a small share of forests, where uncertainty in forest harvesting values may lead to high intensity values (e.g., Northern Italy, see Fig. 1a). Fourth, we used the most recent estimates of industrial roundwood and fuelwood (FAOSTAT, 2012) but this may exclude some unrecorded wood removals. Steierer (2010) found that, at the European level, 27 million m^3 or 4% of the total wood supply (forests, outside forests, and industry) was unrecorded. Furthermore, illegal logging activities mainly taking place in Eastern Europe (Knorn et al., 2012; WWF, 2007) could not be accounted for in our target variable. Thus, officially available data may underestimate real harvested timber volumes locally and thus forest harvesting intensity. Fifth, the time period we analysed is relatively short compared to average rotation lengths of tree species used for harvesting. Ultimately, we could not quantify uncertainty introduced by the use of different data sets since not all predictors used in this analysis were or even can be validated. We selected the, to our knowledge, best products available that served our thematic (hypothesised influence on forest harvesting intensity) and technical requirements (pan-European coverage, NUTS-level or 1 km^2 spatial resolution). While some of the spatial datasets used in our study were validated (e.g., the forest extent map), statistical data is generally collected and provided without uncertainty estimates.

Fostering more sustainable forest use in light of the growing demands for timber products is a grand challenge and ensuring that future intensification of forest management is sustainable would require considering a range of indicators that address the different facets of forest management intensity. Duly considering the multi-dimensionality of sustainable forest management appears particularly important considering the potentially non-linear responses we found. Our results have several practical implications for policy makers seeking to balance forest resource use and the conservation of forest ecosystems and biodiversity. First, the bulk of regions in Europe we investigated in this study were characterised by forest harvesting intensities well below the increment, indicating potential for increasing timber yields through intensification. Hence, sustainable intensification may be possible for many regions in Europe in regards to a key indicator: forest harvesting intensity as the ratio of harvested timber to increment volumes. Second, our results suggest that increasing outputs from forestry may be conceivable without altering tree species composition or introduction of new plantation areas, a management practice known to be generally harmful for local biodiversity (Brockerhoff et al., 2008). For example, existing stands could be managed more intensely, especially in Central Europe, although this may lead to increased carbon emissions, biodiversity loss, the reduction of the carbon sink from current forest ecosystems, and degraded forest recreational values due to altered stand naturalness and age structure (Edwards et al., 2010). Third, future policies could focus on extending plantation areas or improving infrastructural accessibility in important timber-producing regions to lower pressure for intensification in other areas. In that way, such analyses can help identifying sustainable solutions by supporting management decisions and landscape architecture (Turner et al., 2013). Fourth, though the majority of the most important spatial determinants of intensity patterns found in our study were static and cannot easily be changed (e.g., terrain ruggedness, growing stock, forest cover, infrastructure), the two most important determinants we identified provide levers to policy makers and land use planners: plantation species cover and country specific characteristics. Knowing that high forest harvesting intensity relates to high planation share offers action space to modify existing forest management. For example, regions with a large cover of plantation species (especially the Mediterranean countries and western France) could be managed more intensely while considering issues related to biodiversity, environment, and society. Furthermore, a multitude of country specific characteristics, for example forest legislation, policies, or subsidies, promise prospects to influence forest harvesting intensity.

A better understanding of the spatial patterns of forest harvesting intensity and the drivers that produce these patterns are important for understanding the trade-offs between forestry and conservation, and thus ultimately to implement more sustainable forestry systems. Here, we investigated spatial determinants of continental-scale forestry harvesting intensity patterns. We highlight the potential of such analyses to provide insights beyond traditional studies on harvested timber volumes alone and to identify candidate regions and potential levers to sustainable intensification of forestry. Similar to agricultural systems, the question whether to intensify forest use and conservation in a land sparing approach or to integrate forest use and conservation goals in land sharing landscapes becomes an important question for land use and conservation planners (Tscharntke et al., 2012; Edwards et al., 2013). Clearly, there is no silver bullet to this question, but regional-scale analyses such as ours are an important prerequisite to better understanding where and which strategy could be implemented and what the potential benefits and trade-offs of both strategies are. Our continental-scale study provides a starting point for investigating global forest harvesting intensity. To achieve this, it would be interesting to compare our results with those from studies from other world regions. Finally, our study highlights the value of non-parametric approaches to provide new insights into the determinants of forestry intensity and the usefulness of such analysis to inform forest managers, land use planners, and conservation agencies concerned with the spatial targeting of forest policies or investments.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.foreco.2013.12.030.

References

Adams, D.M., Binkley, C.S., Cardellichio, P.A., 1991. Is the level of national forest timber harvest sensitive to price? Land Econ. 67, 74–84.
Amacher, G.S., Conway, M.C., Sullivan, J., 2003. Econometric analyses of nonindustrial forest landowners: is there anything left to study? J. For. Econ. 9, 137–164.
Arano, K.G., Munn, I.A., 2006. Evaluating forest management intensity: a comparison among major forest landowner types. For. Pol. Econ. 9, 237–248.
Baumann, M., Kuemmerle, T., Elbakidze, M., Ozdogan, M., Radeloff, V.C., Keuler, N.S., Prishchepov, A.V., Kruhlov, I., Hostert, P., 2011. Patterns and drivers of post-

socialist farmland abandonment in Western Ukraine. Land Use Pol. 28, 552–562.
Beach, R.H., Pattanayak, S.K., Yang, J.C., Murray, B.C., Abt, R.C., 2005. Econometric studies of non-industrial private forest management: a review and synthesis. For. Pol. Econ. 7, 261–281.
Bengtsson, J., Nilsson, S.G., Franc, A., Menozzi, P., 2000. Biodiversity, disturbances, ecosystem function and management of European forests. For. Ecol. Manage. 132, 39–50.
Böttcher, H., Verkerk, P.J., Gusti, M., HavlÍk, P., Grassi, G., 2012. Projection of the future EU forest CO_2 sink as affected by recent bioenergy policies using two advanced forest management models. GCB Bioenergy 4, 773–783.
Breiman, L., 2001a. Random forests. Mach. Learn. 45, 5–32.
Breiman, L., 2001b. Statistical modeling: the two cultures. Stat. Sci. 16, 199–215.
Brockerhoff, E.G., Jactel, H., Parrotta, J.A., Quine, C.P., Sayer, J., 2008. Plantation forests and biodiversity: oxymoron or opportunity? Biodivers. Conserv. 17, 925–951.
Brus, D.J., Hengeveld, G.M., Walvoort, D.J.J., Goedhart, P.W., Heidema, A.H., Nabuurs, G.J., Gunia, K., 2012. Statistical mapping of tree species over Europe. Eur. J. For. Res. 131, 145–157.
Ciais, P., Schelhaas, M.J., Zaehle, S., Piao, S.L., Cescatti, A., Liski, J., Luyssaert, S., Le-Maire, G., Schulze, E.D., Bouriaud, O., Freibauer, A., Valentini, R., Nabuurs, G.J., 2008. Carbon accumulation in European forests. Nat. Geosci. 1, 425–429.
Crase, B., Liedloff, A.C., Wintle, B.A., 2012. A new method for dealing with residual spatial autocorrelation in species distribution models. Ecography 35, 879–888.
Dearing, J.A., Braimoh, A.K., Reenberg, A., Turner, B.L., van der Leeuw, S., 2010. Complex land systems: the need for long time perspectives to assess their future. Ecol. Soc. 15.
De'ath, G., Fabricius, K.E., 2000. Classification and regression trees: a powerful yet simple technique for ecological data analysis. Ecology 81, 3178–3192.
Department of Agriculture Food & the Marine, s.a. Sitka spruce. Dublin, Irleand. <http://www.agriculture.gov.ie/media/migration/forestry/publications/SitkaSpruce_low.pdf> (accessed 16.06.13).
Dormann, C.F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J.R.G., Gruber, B., Lafourcade, B., Leitão, P.J., Münkemüller, T., McClean, C., Osborne, P.E., Reineking, B., Schröder, B., Skidmore, A.K., Zurell, D., Lautenbach, S., 2013. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography 36, 027–046.
Driessen, P., Deckers, J., Nachtergaele, F., 2001. Lecture Notes on the Major Soils of the World. Food and Agriculture Organization of the United Nations (FAO), Rome, Itlay (accessed 23.03.12).
Duncker, P.S., Barreiro, S.M., Hengeveld, G.M., Lind, T., Mason, W.L., Ambrozy, S., Spiecker, H., 2012. Classification of forest management approaches: a new conceptual framework and its applicability to European forestry. Ecol. Soc. 17.
EC, 2006. European Soil Database v. 2.0. European Commission – DG Joint Research Centre, Ispra, Italy. <http://eusoils.jrc.ec.europa.eu/ESDB_Archive/ESDB> (accessed 10.10.12).
EC, 2012. Regional Statistics by NUTS Classification. European Commission – DG Eurostat, Plateau du Kirchberg, Luxemburg. <http://epp.eurostat.ec.europa.eu/portal/page/portal/statistics/search_database> (accessed 01.10.12).
EC, 2013. Statistics & Market Observatory: Oil Bulletin. European Commission – DG Energy and Transport, Brussels, Belgium. <http://ec.europa.eu/energy/observatory/oil/bulletin_en.htm> (accessed 08.02.13).
Edwards, D., Jay, M., Jensen, F., Lucas, B., Marzano, M., Montagne, C., Peace, A. Weiss, G., 2010. Assessment of the Recreational Value of European Forest Management Alternatives. EFORWOOD Project Deliverable D2.3.6.
Edwards, D.P., Gilroy, J.J., Woodcock, P., Edwards, F.A., Larsen, T.H., Andrews, D.J.R., Derhé, M.A., Docherty, T.D.S., Hsu, W.W., Mitchell, S.L., Ota, T., Williams, L.J., Laurance, W.F., Hamer, K.C., Wilcove, D.S., 2013. Land-sharing versus land-sparing logging: Reconciling timber extraction with biodiversity conservation. Glob. Change Biol. (advance online publication).
EEA, 2010. A Revised Urban–rural Typology. European Environment Agency, Copenhagen. <http://epp.eurostat.ec.europa.eu/statistics_explained/index.php/Urban-rural_typology> (accessed 17.01.13).
EEA, 2011. Nationally Designated Areas (National – CDDA). European Environment Agency, Copenhagen. <http://www.eea.europa.eu/data-and-maps/data/ds_resolveuid/1ec5cbd6ab3294e2e7fe6558cd81b940> (accessed 22.03.12).
Elith, J., Graham, C.H., Anderson, R.P., Dudik, M., Ferrier, S., Guisan, A., Hijmans, R.J., Huettmann, F., Leathwick, J.R., Lehmann, A., Li, J., Lohmann, L.G., Loiselle, B.A., Manion, G., Moritz, C., Nakamura, M., Nakazawa, Y., Overton, J.M., Peterson, A.T., Phillips, S.J., Richardson, K., Scachetti-Pereira, R., Schapire, R.E., Soberon, J., Williams, S., Wisz, M.S., Zimmermann, N.E., 2006. Novel methods improve prediction of species' distributions from occurrence data. Ecography 29, 129–151.
Elith, J., Leathwick, J.R., Hastie, T., 2008. A working guide to boosted regression trees. J. Anim. Ecol. 77, 802–813.
Erb, K.H., 2012. How a socio-ecological metabolism approach can help to advance our understanding of changes in land-use intensity. Ecol. Econ. 76, 8–14.
Erb, K.H., Haberl, H., Jepsen, M.R., Kuemmerle, T., Lindner, M., Müller, D., Verburg, P.H., Reenberg, A., 2013. A conceptual framework for analysing and measuring land-use intensity. Curr. Opin. Environ. Sust. (advance online publication).
FAOSTAT, 2012. Roundwood Production Quantity. Food and Agriculture Organization of the United Nations. <http://faostat.fao.org/site/626/DesktopDefault.aspx?PageID=626#ancor> (accessed 24.01.12).
Foley, J.A., Ramankutty, N., Brauman, K.A., Cassidy, E.S., Gerber, J.S., Johnston, M., Mueller, N.D., O/'Connell, C., Ray, D.K., West, P.C., Balzer, C., Bennett, E.M., Carpenter, S.R., Hill, J., Monfreda, C., Polasky, S., Rockstrom, J., Sheehan, J., Siebert, Zaks, D., Tilman, D.P.M., . Solutions for a cultivated planet. Nature 478, 337–342.
Folke, C., 2006. Resilience: the emergence of a perspective for social-ecological systems analyses. Glob. Environ. Change 16, 253–267.
Forest Europe, UNECE FAO, 2011. State of Europe's Forests 2011: Status and Trends in Sustainable Forest Management in Europe. Ministerial Conference on the Protection of Forests in Europe, Aas, Norway, p. 337.
Friedman, J.H., 2001. Greedy function approximation: a gradient boosting machine. Ann. Stat. 29, 1189–1232.
Friedman, J., Hastie, T., Tibshirani, R., 2000. Additive logistic regression: a statistical view of boosting. Ann. Stat. 28, 337–374.
Gallaun, H., Zanchi, G., Nabuurs, G.-J., Hengeveld, G., Schardt, M., Verkerk, P.J., 2010. EU-wide maps of growing stock and above-ground biomass in forests based on remote sensing and field measurements. For. Ecol. Manage. 260, 252–261.
Gamfeldt, L., Snall, T., Bagchi, R., Jonsson, M., Gustafsson, L., Kjellander, P., Ruiz-Jaen, M.C., Froberg, M., Stendahl, J., Philipson, C.D., Mikusinski, G., Andersson, E., Westerlund, B., Andren, H., Moberg, F., Moen, J., Bengtsson, J., 2013. Higher levels of multiple ecosystem services are found in forests with more tree species. Nat. Commun. 4, 1340.
Gardiner, B., Blennow, K., Carbus, J.-M., Fleischer, P., Ingemarson, F., Landmann, G., Lindner, M., Marzano, M., Nicoll, B., Orazio, C., Peyron, J.-L., Reviron, M.-P., Schelhaas, M.-J., Schuck, A., Spielmann, M., Usbeck, T., 2010. Destructive Storms in European Forests: Past and Forthcoming Impacts. European Forest Institute, p. 138.
Gellrich, M., Baur, P., Robinson, B.H., Bebi, P., 2008. Combining classification tree analyses with interviews to study why sub-alpine grasslands sometimes revert to forest: a case study from the Swiss Alps. Agric. Syst. 96, 124–138.
Haberl, H., Erb, K.H., Krausmann, F., Gaube, V., Bondeau, A., Plutzar, C., Gingrich, S., Lucht, W., Fischer-Kowalski, M., 2007. Quantifying and mapping the human appropriation of net primary production in earth's terrestrial ecosystems. Proc. Natl. Acad. Sci. 104, 12942–12947.
Hartley, M.J., 2002. Rationale and methods for conserving biodiversity in plantation forests. For. Ecol. Manage. 155, 81–95.
Hastie, T., Tibshirani, R., Friedman, J.H., 2011. The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer-Verlag, New York, p. 744.
Hengeveld, G.M., Nabuurs, G.-J., Didion, M., van den Wyngaert, I., Clerkx, A.P.P.M., Schelhaas, M.-J., 2012. A forest management map of European forests. Ecol. Soc. 17.
Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. Int. J. Climatol. 25, 1965–1978.
Hijmans, R.J., Phillips, S., Leathwick, J.R., Elith, J., 2013. dismo: Species Distribution Modeling. <http://cran.r-project.org/web/packages/dismo/> (accessed 02.04.13).
IUCN UNEP-WCMC, 2012. The World Database on Protected Areas (WDPA). UNEP-WCMC, Cambridge, UK. <www.protectedplanet.net> (accessed 01.02.12).
Jandl, R., Lindner, M., Vesterdal, L., Bauwens, B., Baritz, R., Hagedorn, F., Johnson, D.W., Minkkinen, K., Byrne, K.A., 2007. How strongly can forest management influence soil carbon sequestration? Geoderma 137, 253–268.
Kaplan, J.O., Krumhardt, K.M., Zimmermann, N.E., 2012. The effects of land use and climate change on the carbon cycle of Europe over the past 500 years. Glob. Change Biol. 18, 902–914.
Kendall, M.G., 1938. A new measure of rank correlation. Biometrika 30, 81–93.
Knorn, J., Kuemmerle, T., Radeloff, V.C., Szabo, A., Mindrescu, M., Keeton, W.S., Abrudan, I., Griffiths, P., Gancz, V., Hostert, P., 2012. Forest restitution and protected area effectiveness in post-socialist Romania. Biol. Conserv. 146, 204–212.
Kuemmerle, T., Erb, K., Meyfroidt, P., Müller, D., Verburg, P.H., Estel, S., Haberl, H., Hostert, P., Jepsen, M.R., Kastner, T., Levers, C., Lindner, M., Plutzar, C., Verkerk, P.J., van der Zanden, E.H., Reenberg, A., 2013. Challenges and opportunities in mapping land use intensity globally. Curr. Opin. Environ. Sust. (advance online publication).
Kuusela, K., 1994. Forest Resources in Europe. Cambridge University Press, Cambridge, USA, p. 172.
Lakes, T., Müller, D., Krüger, C., 2009. Cropland change in southern Romania: a comparison of logistic regressions and artificial neural networks. Landscape Ecol. 24, 1195–1206.
Lambin, E.F., Meyfroidt, P., 2011. Global land use change, economic globalization, and the looming land scarcity. Proc. Natl. Acad. Sci. 108, 3465–3472.
Lambin, E.F., Turner, B.L., Geist, H.J., Agbola, S.B., Angelsen, A., Bruce, J.W., Coomes, O.T., Dirzo, R., Fischer, G., Folke, C., George, P.S., Homewood, K., Imbernon, J., Leemans, R., Li, X., Moran, E.F., Mortimore, M., Ramakrishnan, P.S., Richards, J.F., Skånes, H., Steffen, W., Stone, G.D., Svedin, U., Veldkamp, T.A., Vogel, C., Xu, J., 2001. The causes of land-use and land-cover change: moving beyond the myths. Glob. Environ. Change 11, 261–269.
Leathwick, J.R., Elith, J., Francis, M.P., Hastie, T., Taylor, P., 2006. Variation in demersal fish species richness in the oceans surrounding New Zealand: an analysis using boosted regression trees. Mar. Ecol. Prog. Ser. 321, 267–281.
Lin, Y.-P., Chu, H.-J., Wu, C.-F., Verburg, P.H., 2011. Predictive ability of logistic regression, auto-logistic regression and neural network models in empirical land-use change modeling – a case study. Int. J. Geogr. Inform. Sci. 25, 65–87.
Luyssaert, S., Hessenmöller, D., von Lüpke, N., Kaiser, S., Schulze, E.D., 2011. Quantifying land use and disturbance intensity in forestry, based on the self-thinning relationship. Ecol. Appl. 21, 3272–3284.
Luyssaert, S., Abril, G., Andres, R., Bastviken, D., Bellassen, V., Bergamaschi, P., Bousquet, P., Chevallier, F., Ciais, P., Corazza, M., Dechow, R., Erb, K.H., Etiope, G.,

Fortems-Cheiney, Grassi, G., Hartmann, J., Jung, M., Lathière, J., Lohila, A., Mayorga, E., Moosdorf, N., Njakou, D.S., Otto, J., Papale, D., Peters, W., Peylin, P., Raymond, P., Rödenbeck, C., Saarnio, S., Schulze, E.D., Szopa, S., Thompson, R., Verkerk, P.J., Vuichard, N., Wang, R., Wattenbach, M., Zaehle, S., 2007. The European land and inland water CO_2, CO, CH_4 and N_2O balance between 2001 and 2005. Biogeosciences 9, 3357–3380.
MA, 2005. Ecosystems and Human Well-being: Current State and Trends. Island Press, Washington, DC, p. 137.
Metzger, M.J., Leemans, R., Schröter, D., 2005. A multidisciplinary multi-scale framework for assessing vulnerabilities to global change. Int. J. Appl. Earth Obs. Geoinf. 7, 253–267.
Moran, P.A.P., 1950. Notes on continuous stochastic phenomena. Biometrika 37, 17–23.
Müller, R., Müller, D., Schierhorn, F., Gerold, G., 2011. Spatiotemporal modeling of the expansion of mechanized agriculture in the Bolivian lowland forests. Appl. Geogr. 31, 631–640.
Müller, D., Leitao, P.J., Sikor, T., 2013. Comparing the determinants of cropland abandonment in Albania and Romania using boosted regression trees. Agric. Syst. 117, 66–77.
Munn, I.A., Barlow, S.A., Evans, D.L., Cleaves, D., 2002. Urbanization's impact on timber harvesting in the south central United States. J. Environ. Manage. 64, 65–76.
Nabuurs, G.-J., Lindner, M., Verkerk, P.J., Gunia, K., Deda, P., Michalak, R., Grassi, G., 2013. First signs of carbon sink saturation in European forest biomass. Nat. Clim. Change (advance online publication).
NASA, 2006. Shuttle Radar Topography Mission. <http://www.jpl.nasa.gov/srtm> (accessed 08.08.06).
Nelson, A., 2008. Estimated Travel Time to the Nearest City of 50,000 or more People in year 2000. Global Environment Monitoring Unit – Joint Research Centre of the European Commission, Ispra, Italy. <http://bioval.jrc.ec.europa.eu/products/gam/index.htm> (accessed 13.07.11).
New, M., Lister, D., Hulme, M., Makin, I., 2002. A high-resolution data set of surface climate over global land areas. Clim. Res. 21, 1–25.
Paillet, Y., Berges, L., Hjalten, J., Odor, P., Avon, C., Bernhardt-Roemermann, M., Bijlsma, R.J., De Bruyn, L., Fuhr, M., Grandin, U., Kanka, R., Lundin, L., Luque, S., Magura, T., Matesanz, S., Meszaros, I., Teresa Sebastia, M., Schmidt, W., Standovar, T., Tothmeresz, B., Uotila, A., Valladares, F., Vellak, K., Virtanen, R., 2010. Biodiversity differences between managed and unmanaged forests: meta-analysis of species richness in Europe. Conserv. Biol. 24, 101–112.
Pekkarinen, A., Reithmaier, L., Strobl, P., 2009. Pan-European forest/non-forest mapping with Landsat ETM+ and CORINE Land Cover 2000 data. Isprs J. Photogram. Rem. Sens. 64, 171–183.
Pereira, H.M., Leadley, P.W., Proenca, V., Alkemade, R., Scharlemann, J.P.W., Fernandez-Manjarras, J.F., Araújo, M.B., Balvanera, P., Biggs, R., Cheung, W.W.L., Chini, L., Cooper, H.D., Gilman, E.L., Guanette, S., Hurtt, G.C., Huntington, H.P., Mace, G.M., Oberdorff, T., Revenga, C., Rodrigues, P., Scholes, R.J., Sumaila, U.R., Walpole, M., 2010. Scenarios for global biodiversity in the 21st century. Science 330, 1496–1501.
Pulla, P., Schuck, A., Verkerk, P.J., Lasserre, B., Marchetti, M., Green, T., 2013. Mapping the Distribution of Forest Ownership in Europe. EFI Technical Report 88. European Forest Institue (EFI), Joensuu, Finland, p. 91.
R Development Core Team, 2012. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. <http://www.R-project.org>.
Riley, S.J., DeGloria, S.D., Elliott, R., 1999. A terrain ruggedness index that quantifies topographic heterogeneity. Int. J. Sci. 5, 23–27.
Rudel, T.K., Coomes, O.T., Moran, E., Achard, F., Angelsen, A., Xu, J., Lambin, E., 2005. Forest transitions: towards a global understanding of land use change. Glob. Environ. Change 15, 23–31.
Schall, P., Ammer, C., 2013. How to quantify forest management intensity in Central European forests. Eur. J. For. Res. 132, 379–396.
Scheffer, M., Carpenter, S.R., Lenton, T.M., Bascompte, J., Brock, W., Dakos, V., van de Koppel, J., van de Leemput, I.A., Levin, S.A., van Nes, E.H., Pascual, M., Vandermeer, J., 2012. Anticipating critical transitions. Science 338, 344–348.
Schuck, A., van Brusselen, J., Päivinen, R., Häme, T., Kennedy, P., Folving, S., 2002. Compilation of a Calibrated European Forest Map derived from NOAA-AVHRR Data. EFI Internal Report 13, European Forest Institute, Joensuu.
Seto, K.C., Reenberg, A., Boone, C.G., Fragkias, M., Haase, D., Langanke, T., Marcotullio, P., Munroe, D.K., Olah, B., Simon, D., 2012. Urban land teleconnections and sustainability. Proc. Natl. Acad. Sci. 109, 7687–7692.
Simões, D., Fenner, P.T., 2010. Influence of relief in productivity and costs of harvester. Sci. Forest. 38, 107–114.
Steierer, F., 2010. EU/EFTA Sub-regional and National Wood Resource Balances 2005. Geneva Timber and Forest Study Paper 51, United Nations Economic Commission for Europe/Food and Agriculture Organization of the United Nations, Geneva, Switzerland, p. 60.
Størdal, S., Lien, G., Baardsen, S., 2008. Analyzing determinants of forest owners' decision-making using a sample selection framework. J. For. Econ. 14, 159–176.
Tilman, D., Balzer, C., Hill, J., Befort, B.L., 2011. Global food demand and the sustainable intensification of agriculture. Proc. Natl. Acad. Sci. 108, 20260–20264.
Tscharntke, T., Clough, Y., Wanger, T.C., Jackson, L., Motzke, I., Perfecto, I., Vandermeer, J., Whitbread, A., 2012. Global food security, biodiversity conservation and the future of agricultural intensification. Biol. Conserv. 151, 53–59.
Turner II, B.L., Janetos, A.C., Verburg, P.H., Murray, A.T., 2013. Land system architecture: using land systems to adapt and mitigate global environmental change. Glob. Environ. Change 23, 395–397.
UNECE FAO, 2000. Forest Resources of Europe, CIS, North America, Australia, Japan and New Zealand. Contribution to the Global Forest Resources Assessment 2000. United Nations, Geneva, New York.
UNECE FAO, 2010. Forest Product Conversion Factors For The UNECE Region. Geneva Timber and Forest Discussion Paper 49. United Nations, Geneva, p. 38.
UNECE FAO, 2011. European Forest Sector Outlook Study II – 2010–2030. Geneva Timber and Forest Study Paper 28. United Nations, Geneva.
van Berkel, D.B., Verburg, P.H., 2011. Sensitising rural policy: assessing spatial variation in rural development options for Europe. Land Use Pol. 28, 447–459.
van Putten, I., Jennings, S., 2010. Modeling forest owner harvesting behaviour and future intentions in Tasmania. Small-Scale Forest. 9, 175–193.
Verburg, P.H., van de Steeg, J., Veldkamp, A., Willemen, L., 2009. From land cover change to land function dynamics: a major challenge to improve land characterization. J. Environ. Manage. 90, 1327–1335.
Verkerk, P.J., Anttila, P., Eggers, J., Lindner, M., Asikainen, A., 2011. The realisable potential supply of woody biomass from forests in the European Union. For. Ecol. Manage. 261, 2007–2015.
Vilén, T., Gunia, K., Verkerk, P.J., Seidl, R., Schelhaas, M.J., Lindner, M., Bellassen, V., 2012. Reconstructed forest age structure in Europe 1950–2010. For. Ecol. Manage. 286, 203–218.
von Carlowitz, H.C., 1713. Sylvicultura Oeconomica. Leipzig, p.
Wear, D.N., Liu, R., Michael Foreman, J., Sheffield, R.M., 1999. The effects of population growth on timber management and inventories in Virginia. For. Ecol. Manage. 118, 107–115.
Wendland, K.J., Lewis, D.J., Alix-Garcia, J., Ozdogan, M., Baumann, M., Radeloff, V.C., 2011. Regional- and district-level drivers of timber harvesting in European Russia after the collapse of the Soviet Union. Glob. Environ. Change 21, 1290–1300.
Wu, J., 2013. Landscape sustainability science: ecosystem services and human well-being in changing landscapes. Landscape Ecol., 1–25.
WWF, 2007. Forest Illegal Logging. <http://www.panda.org/about_wwf/what_we_do/forests/problems/forest_illegal_logging/index.cfm> (accessed 11.08.08].