Local forest harvesting patterns in Europe predicted through regression modeling

There are significant regional differences in the volume and intensity of forest harvesting in Europe. Due to environmental and socioeconomic conditions both the available forest area as well as the management structures differ considerably. As the demand for forest products grows and ecosystem productivity is distributed unevenly, the question of sustainability of forestry activities has to be addressed on a local scale. Yet, there is a lack of regionalized data on forest harvesting volumes and intensities combined on a continental scale. In order to gain a better understanding of the relationship between forest harvesting and its spatial drivers, this study is using regression modeling techniques to identify environmental and socioeconomic determinants governing local forest use. Based on a regression model, localized predictions will be produced, helping to identify overall patterns and local hotspots of forest harvesting volume and intensity.

Keywords: forest, harvesting, harvesting intensity, regression, modeling, Europe

1. **Introduction**

Different land use is the main sustenance of humanity. With a general global trend of increasing demand for products land use and its production have to intensify with the challenge to manage in a sustainable way [19]. In forestry this increasing demand for products, that supply humanity with important raw materials, results in an increasing production and regional differences in volume and intensity. The intensification of production in forestry can only operate with an understanding of the spatial patterns of forest management intensity and the drivers that produce these patterns [19]. The forest management intensity is a complex term dependent on a lot of indicators (e.g. harvested timber volumes, forest structure) that affect forest structure [36], soils [17], biogeochemical cycles [23, 21], biodiversity [28], and ecosystem service provisioning [13]. In Europe forestry has a long history. In the 19th and 20th century Europe's forests have gained in area after centuries of extensive deforestation (0.37% per year [11]) and cover 37% of the surface. Forest cover distribution is very unevenly in Europe and influenced by climatic, environmental, historical, ethnic, and economic heterogeneity. The averaged forest harvesting intensity also increased (58% in 1990, 62.4% in 2010 [11]). The sustainable intensification of forest management requires a range of indicators addressing the multidimensionality of forest management intensity.

This study analyses local forest harvesting patterns in Europe based on forest harvesting data and a selection of possible drivers. The goal is a prediction of forest harvesting patterns in a high resolution across Europe through regression modelling. Former studies only focussed on single national scales or regions. By building a regression model and using it to predict local harvesting volumes we want to address the following research questions:

- 1. Which drivers govern harvesting volume and intensity in Europe?
- 2. What are the spatial patterns of forest use? Where are local hotspots?
- 3. How sustainable is the local forest use?

2. Material and Methods

2.1 Data

2.1.1 Forest Harvesting Data

To investigate spatial patterns and drivers of forest use, reported forest harvesting volumes for Norway, Switzerland and all EU27 countries are available at different administrative units ranging from national to district level (NUTS 0-3) as collected by Levers et al. 2014 [19]. Overall, a total of 460 administrative units across Europe are covered. This harmonized dataset, corrected for differences in data collection across regions and administrative units includes the average officially reported harvested volumes between 2000 and 2010 as m³/ha of roundwood removed under bark- and fuelwood [10].

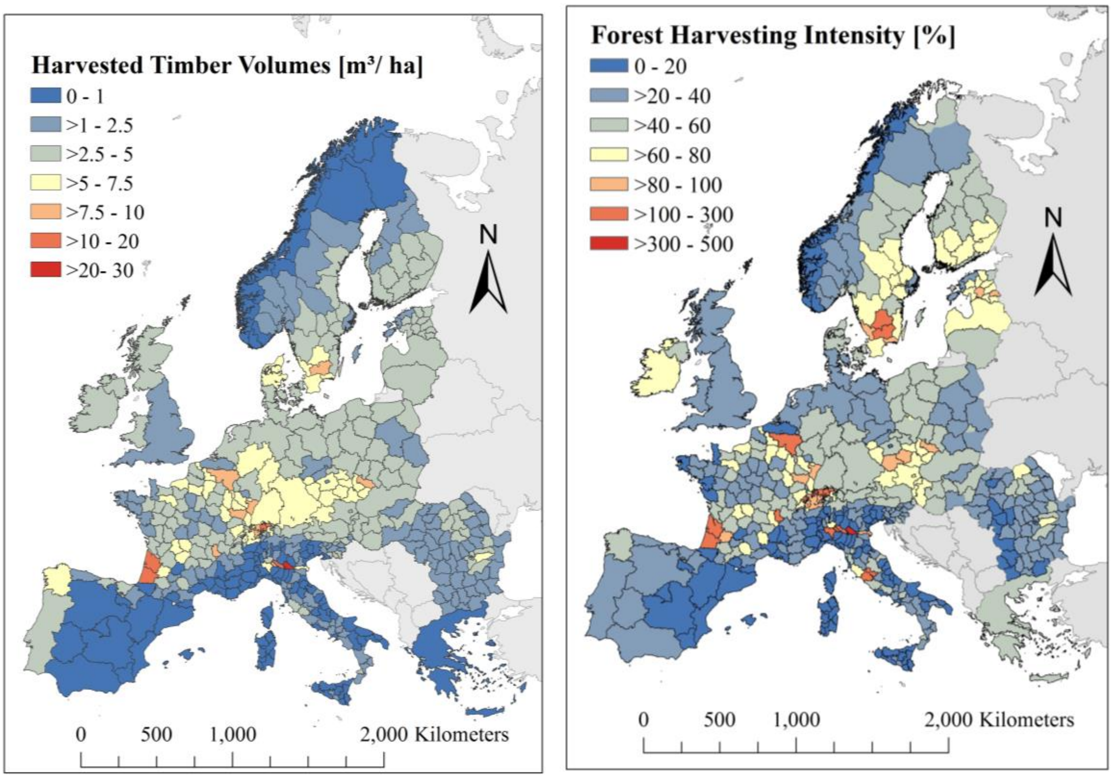


Fig. 1(a) (left): Harvested timber volumes in the administrative units investigated.

Fig. 1(b) (right): Forest harvesting intensity in the administrative unites investigated.

At the time of writing, this dataset represents the only available providing recent numbers of harvesting volume on a regional scale in Europe as officially reported. However, the resolution of administrative units on which harvested volumes are collected differ strongly by country and do not include forest losses due to illegal logging or other causes (e.g. storms or forest fires).

Moreover, regional data (NUTS 0-2) of forest regrowth is available as net annual increment (NAI) in m^3/ha. By dividing the reported harvested volumes with expected ecosystem productivity (NAI values), the resulting index of harvesting intensity in percent can be used to measure the sustainability of forest use, illustrating the relation between the extraction of timber and the regeneration capacity of the forest ecosystem [19].

2.1.1 Predictor Variables

To investigate the spatial determinants governing patterns of forest harvesting volumes, datasets of 17 possible drivers are used. These include data on forest resources and management structure, environmental as well as demographic and socioeconomic conditions, all of which are available as raster layers with a spatial resolution of 1km. Table 1 gives an overview of all datasets employed as possible predictor variables.

In order to account for differences in policy, governance and forest management structures at the nation level, the country can be used as a dummy variable in the regression models. The predictor datasets were collected by Levers et al. 2014 [19]. For detailed information on data sources see Tab.1.
Because of the higher spatial resolution of the predictor raster datasets, they had to be aggregated on the administrative units of the forest harvesting data in order to build a

Tab. 1: Overview of datasets available as predictor variables.

Factor	Predictor Name	Description	Unit	Source
Forest resources	BEECHOAK	Share of beech (*Fagus spp.*) and oak (*Quercus spp.*) in total species	%	[3]
	FCOV	Forest cover	%	[29, 3, 33]
	NAI	Net annual increment of forest biomass	m³/ha	[11]
	PINESPRUCE	Share of pine (*Pinus sylvestris*) and spruce (*Picea spp.*) in total species	%	[3]
	PLANTATION	Share of plantation species (*Robinia spp., Populus spp., Eucalyptus spp., Pinus pinaster*) in total species	%	[3]
	PRIVFOR	Share of privately owned forest in total forest	%	[30]
	TOTPROT	Share of protected forest in total forest	%	[35, 9]
	TOTVOL	Total growing stock	m³/ha	[12]
Environmental Conditions	POORSOIL	Share of low productive soil limiting growth	%	[7, 8, 35]
	PRCP5M	Precipitation sums of growing season	mm	[16]
	RUGG	Terrain ruggedness expressing relief energy	m	[24, 35]
	SBC	Share of soil types with no bearing capacity	%	[8, 35]
	TEMP	Long term mean temperature	°C	[16]
	WATSHORT	Difference between precipitation potential and evapotranspiration, both during growing season	mm	[26, 22, 16]
Demography & Socioeconomy	ACC50	Travel time to cities >50,000 inhabitants	min	[25]
	POPDENS2	Population density	pers/km²	[2]
	COUNTRY	Dummy to capture country characteristics	-	-

regression model. Therefore, they are weighted according to the forest cover map by Pekkarinen et al. 2009 [29] in order to exclude irrelevant data points and grade the importance of forest pixels by their partial forest cover. After multiplying the predictors with this cover map, they are aggregated on the spatial units of the target variable as weighted mean values. For two predictor variables, simple mean values were used as aggregates instead of a weighted arithmetic means: forest cover and population density. While forest cover itself depicted the weights used, the influence of population density was expected to be spatially separate from forest cover, as high population density – possibly an indicator of anthropogenic pressure on forest resources – generally does not overlap with forested areas.

2.2 Statistical Model Building and Selection

To aid model selection, a combination of automatic and manual selection approaches was applied. Figure 2 gives a schematic overview of the approach employed for model selection.

In order to define possible candidate models, the results of different best-subset regressions carried out with an algorithm available in the '*MuMIn'* package for R were investigated [1]. In a best subset regression, the performance of all possible models according to an information criterion is evaluated in a model space defined by the analyst [15]. In addition to the 17 predictor variables listed in Tab.1, interaction and nonlinear terms were also considered to be included in the maximum model space.

To determine significant interactions between predictor variables, linear correlation coefficients as well as visual plot analysis was utilized. Based on this method three interaction terms were introduced to the model space: TEMP:PINESPRUCE (linear Pearson correlation r= -0.72), WATSHORT:PRCP5M (r=0.62) and WATSHORT:TEMP (r=-0.61). There is a significant trend of increasing pine and spruce cover with decreasing temperatures (increasing latitude), while there are immediate relations between water shortage and precipitation as well as water shortage and temperature.

Possible nonlinear relationships between harvesting volumes and predictor terms were investigated by visual analysis of plots. However, the use of nonlinear terms was ruled out because no strictly quadratic or cubic relationships were found. Moreover, the inclusion of additional terms causes an exponential growth of the maximum model space and hence computation time. Thus, in order to keep computational requirements within practical dimensions, the maximum model space was limited to 20 variables (17 predictors and three interaction terms).

We compared the performance of two model types: linear ordinary least square (OLS) models as well as generalized linear models (GLMs) with a log link. The latter were regarded a valid alternative to standard linear models because of the heavily skewed distribution of the forest harvesting data. Since the country dummy variable was expected to have a significant impact on the other coefficients in a hypothesized model, models including the country dummy and those not including it were computed separately. As for measures of performance we compared both models selected after AIC and BIC. This way, the linear and log models with the 10 lowest AIC and BIC scores, both with and without the country variable were selected as possible candidate models.

To be able to compare the performance of the linear against the log models and with building a predictive model being the main goal of this study, the generalization error of the subset of candidate models estimated by cross validation was computed as an additional indicator of model performance. Since the dataset was relatively small (460 observations), the resampling technique was preferred over a test-set holdout. Because of the relatively strong volatility of the cross validation error, 5-folds cross validation was repeated 10 times for each model [18].

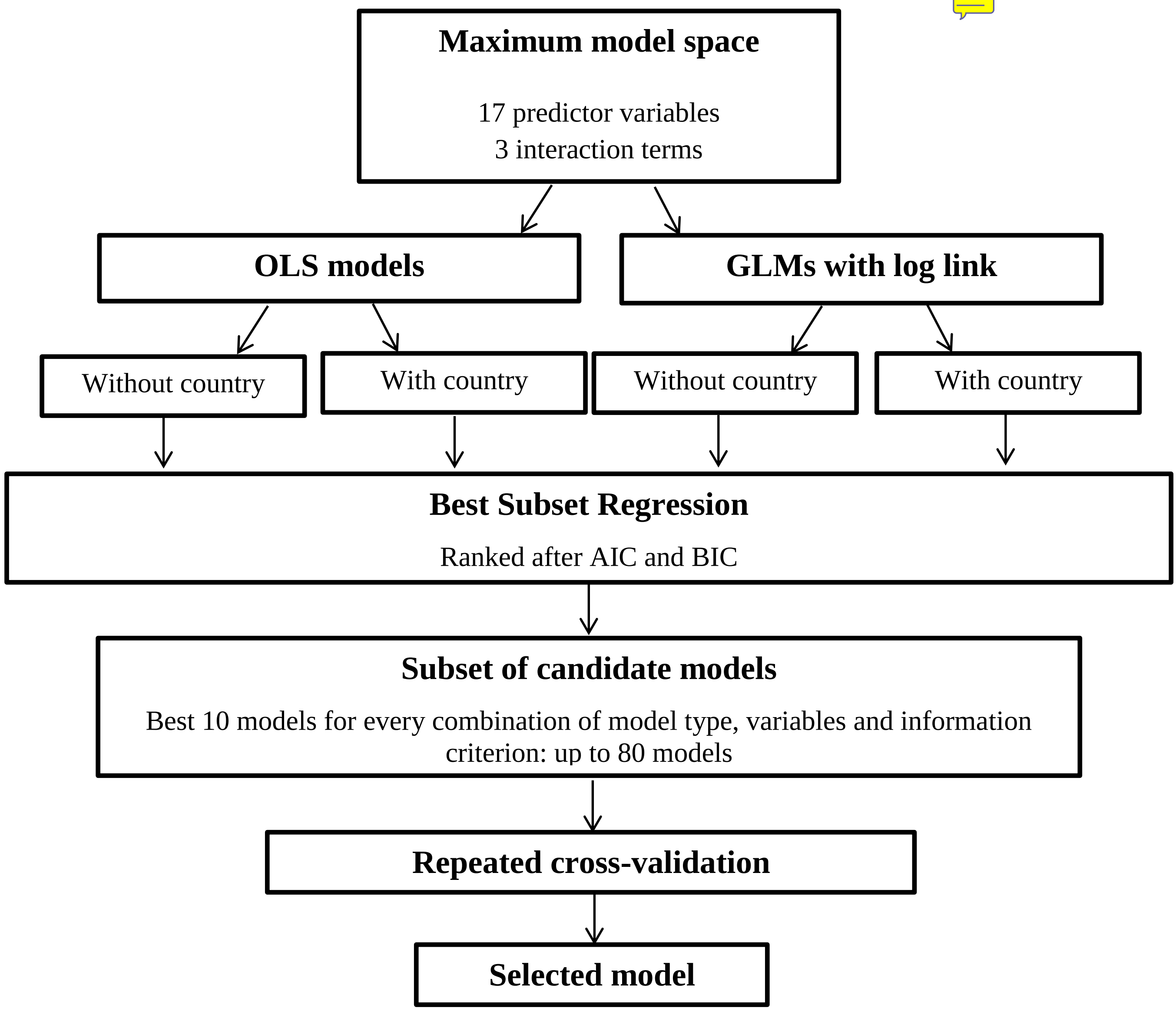


Fig. 2: Schematic overview of the model selection approach.

2.3 Spatial Prediction

The final model selected from the set of candidate models is then used to predict local harvesting volumes and intensities making use of the relatively high resolution of the predictor datasets (1km). The high resolution maps produced can help to identify hotspots of forest harvesting volume. Moreover, by comparing predicted harvesting volumes with NAI data, the sustainability of local forest use across Europe can be assessed.

3. Results and Interpretation

3.1 Model Selection and Performance

As a result of the model selection approach discussed 80 candidate models came into closer consideration. In general models including the country dummy scored better in AIC than models without country dummy. For the BIC the results are vice versa due to the criterion behavior of penalizing model complexity more heavily than the AIC [15]. Fig. 3 shows a representation of the bias-variance tradeoff regarding model complexity, signifying that small models (model size <7) tend to underfit, while larger models (model size > 12) can exhibit overfitting, especially in the case of the log models [15]. For OLS models with the country dummy (*lin.c*) which overall performed best in cross validation error (CV error), the CV error saturates around a model size of 9 from whereon no significant improvements in model performance can be observed.

Among the set candidate models, the final model was selected 'manually' by the analysts, by comparing the performance in AIC, BIC and CV error, general model fit and validity as well as variables included.

The chosen model for prediction is an OLS model with 10 predictor variables, including the country dummy, and none of the three possible variable interactions that were included in the computing process.

The model selected was among the best in cross validation error (CV error: 3.072). Furthermore it had a very good score in the AIC (1817) with a difference of only five points to the best performing model (1812) in this criterion. Moreover it had a relatively low BIC score of 1974 in comparison to the best score of 1971 among the OLS models with country predictor.

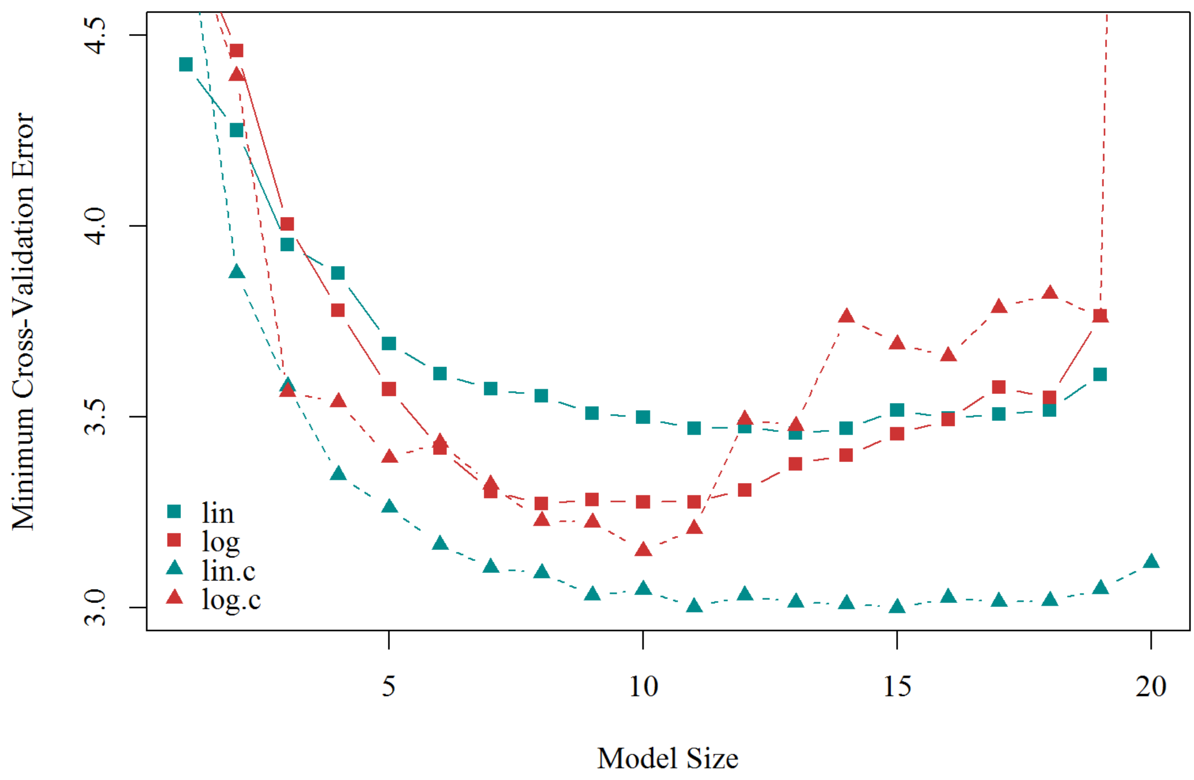


Fig. 3: Model performance as measured by minimum repeated cross validation error (mean squared error) as a function of model size for models selected after AIC and BIC. Different lines represent different model types: OLS models with country dummy (lin.c) and without (lin) are shown in blue, GLMs with log link with country dummy (log.c) and without (log) are shown in red.

As mentioned above, the BIC of the OLS models without country dummy have generally lower BIC values with the best score at 1912. Still, the BIC of the selected model is relatively low in comparison to all other models and model types.

Apart from the very good performance in the three selection criterions the model is parsimonious with only 10 variables. Even more important than the bare number is the fact that the top 7 out of the ten most frequent variables in all of the candidate models were included (See Tab. 2). Of these the top four variables (NAI, PINESPRUCE, PLANTATION, RUGG) were chosen in all 80 of 80 best performing models and COUNTRY was chosen in 40 of 40 best performing models where the country dummy was available. The only predictor in the selected model that was chosen by a fewer number of models (37 out of 80) was the SBC variable, which however was included in 8 out of 10 of the candidate OLS models with country dummy.

Tab. 2: Overview of predictor frequency within candidate models. Predictors included in the selected model are written in bold. The country variable was only available in half of the models.

Model type / Variables	lin AIC	lin.c AIC	log AIC	log.c AIC	lin BIC	lin.c BIC	log BIC	log.c BIC	TOTAL
NAI	10	10	10	10	10	10	10	10	**80**
PINESPRUCE	10	10	10	10	10	10	10	10	**80**
PLANTATION	10	10	10	10	10	10	10	10	**80**
RUGG	10	10	10	10	10	10	10	10	**80**
FCOV2000	10	10	10	10	8	8	9	10	**75**
WATSHORT	10	10	10	10	4	10	10	10	**74**
POPDENS2	0	10	10	10	0	4	2	10	**46**
PRCP5M	10	4	10	1	10	0	10	0	**45**
PRIVFOR	3	10	1	10	0	10	0	10	**44**
ACC50	10	0	10	4	4	0	10	2	**40**
COUNTRY	0	10	0	10	0	10	0	10	**40**
POORSOIL	10	0	10	1	10	0	9	0	**40**
SBC	5	7	2	10	1	3	1	8	**37**
TEMP	3	10	3	10	2	0	0	2	**30**
TOTVOL	0	3	1	10	0	3	0	8	**25**
PRCP5M:WATSHORT	10	1	9	0	3	0	2	0	**25**
BEECHOAK	0	5	10	2	0	1	4	2	**24**
TEMP:WATSHORT	0	9	2	10	0	0	0	1	**22**
PINESPRUCE:TEMP	0	10	1	2	0	0	0	0	**13**
TOTPROT	4	1	2	2	0	0	1	1	**11**

The determination of a single best regression model generally is difficult given a large model space due to the number of multiple good candidate models with similar performance but different advantages by criterion type.

Next to the performance in the criterions used for model selection, absolute model accuracy can be estimated using measures such as R^2 or the Root Mean Squared Error (RMSE). The selected model explained 59% percent of the variation in the original harvesting data (R^2 of 0.59). According to the RMSE, the models' estimates in average deviate by 1.74 m^3/ha (RMSE of 1.74) from the test data sets during cross-validation. These absolute performance measures show that there are considerable errors in the model's estimates, which have to be born in mind when evaluating prediction results. However, such levels of errors are not uncommon for complex ecological problems like the one investigated in this study.

To examine the validity of the selected model, model diagnostics was carried out to check for the general assumptions of Ordinary Least Squares models. The selected model exhibits normally distributed errors and unproblematic levels of multicollinearity with the highest Variance Inflation Factor (VIF) among the numeric variables being 6.2, well below the commonly recommended maximum value of 10 for linear models [27]. The model showed moderate heteroscedasticity, but as parameter estimates and accordingly model predictions are not affected by this problem, the model was deemed to be valid overall [32].

3.2 Predictor Importance and Effects

Among the selected predictors, the country dummy and NAI variable are by far the most influential variables. Fig. 4 shows the relative variable importance according to the contribution of each predictor to the overall R^2 of the model. These were calculated with the *relaimpo*-Package in R [14], which uses a method for decomposing R^2 proposed by Lindemann et al. 1980 [20].

The relationship between the six most important predictors (COUNTRY, NAI, RUGG, PLANTATION, WATSHORT, PINESPRUCE) and harvested timber volumes is displayed in Fig. 5, showing the partial residual plots (also known as component plus residual plots) for these six variables, as the influence of the other four variables included in the model is significantly smaller (s. Fig. 4). Partial residual plots are constructed by plotting separate independent variables against the residuals of the full model plus the respective independent variable multiplied by its regression coefficient [5]. They attempt to show the relationship between the predictor variable and the dependent variable while accounting for the influence of the other independent variables in the model.

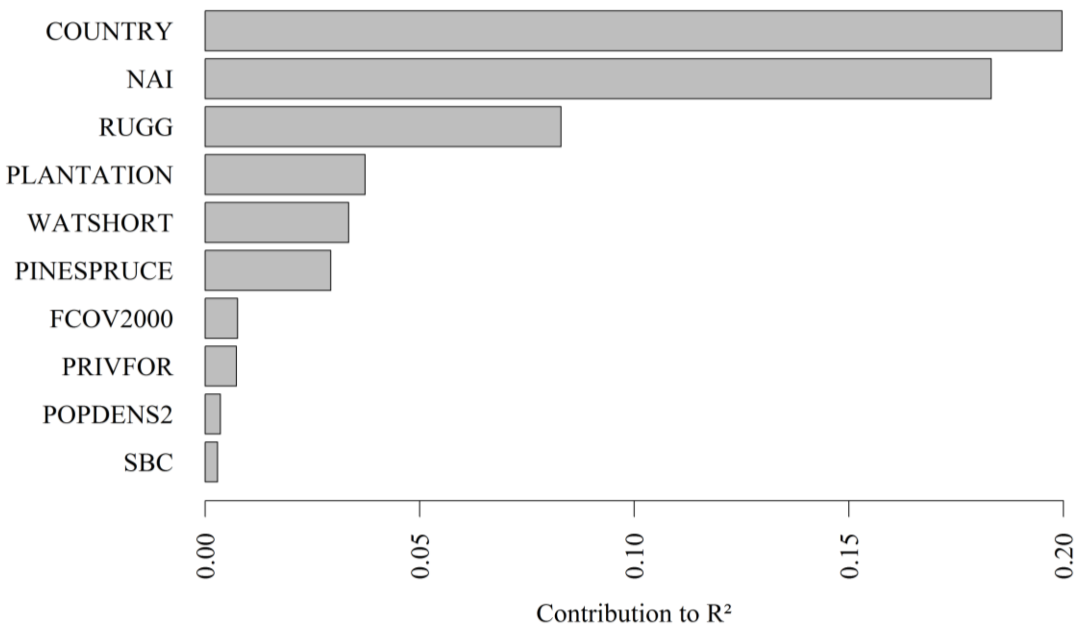


Fig. 4: Variable importance as measured by contribution to R^2.

As expected, the influence of the country variable varies strongly by nation. A clear positive effect on harvesting volumes can be observed for the NAI and PLANTATION variables, even though there are very few observations for large values of the PLANTATION variable. While higher forest ecosystem productivity (NAI) allows for a more intensified forest use, intensive forestry can involve the use of fast growing plantation species (in turn affecting the net annual increment). In contrast, terrain ruggedness has a distinct negative effect on harvesting volume.

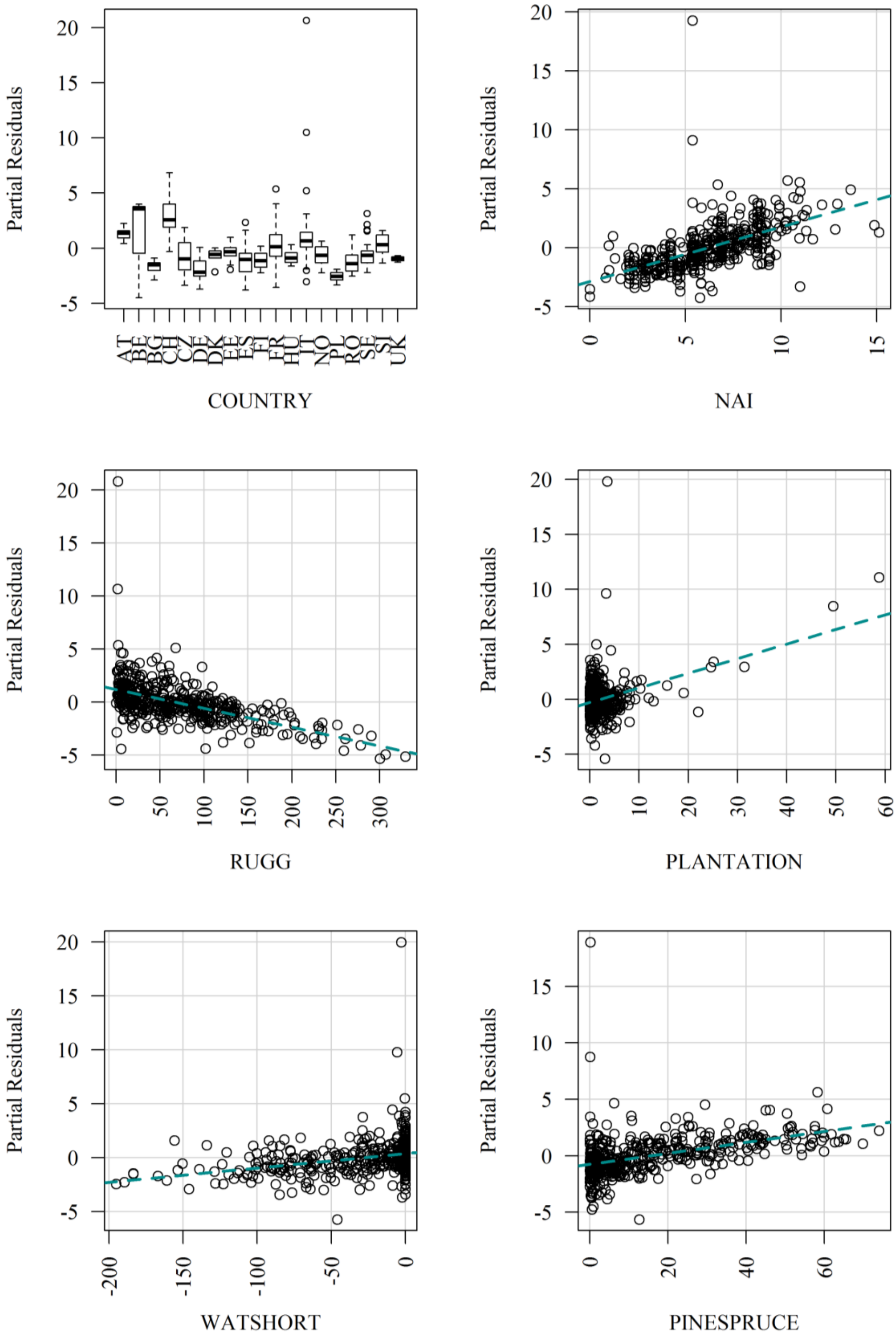
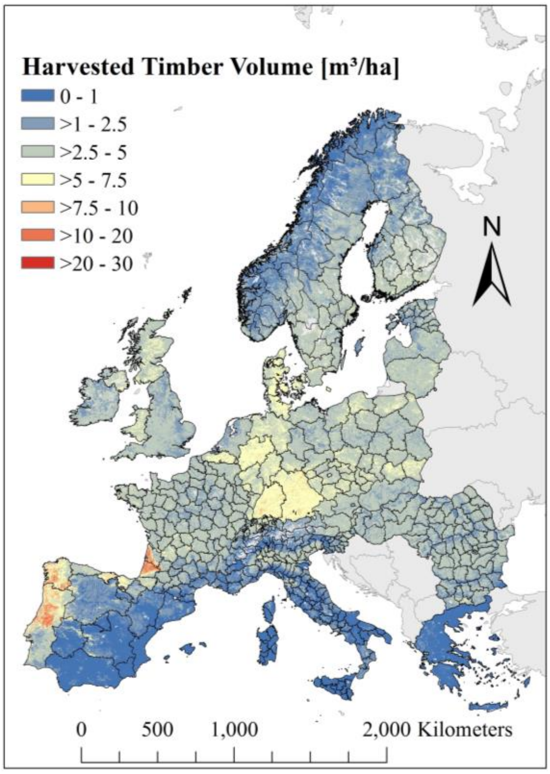


Fig. 5: Partial residual plots (component plus residual plots) for the six most important variables of the selected model.

This is due to fact that forest use in general is constrained in rugged terrain [19]. The effect of the other two predictors on harvesting volumes is less distinct with slightly positive effects of WATSHORT and PINESPRUCE. With smaller differences between precipitation and evapotranspiration (meaning higher values in the WATSHORT variable) more favorable climatic conditions (less water shortage) correlate with higher harvesting volumes. The same is true for higher covers of pine or spruce species, as these are among the most important tree species for industrial forest use in Europe.

3.3 Spatial Prediction Results



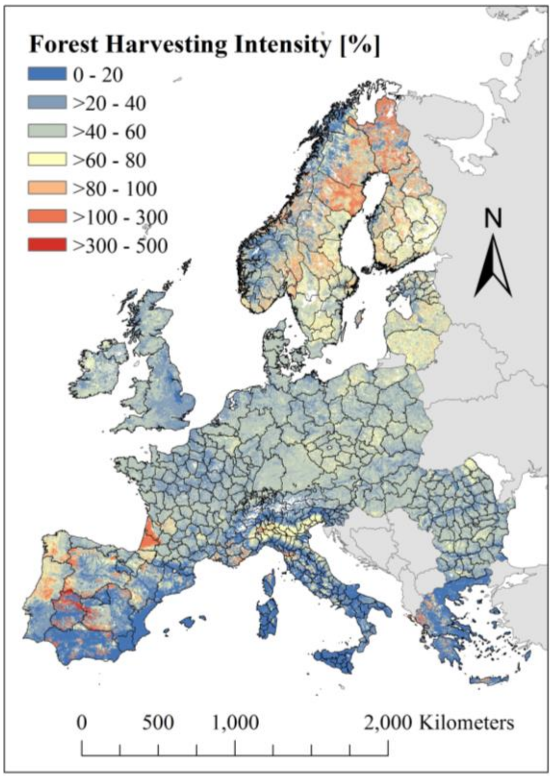


Fig. 6(a) (left): Predicted harvested timber volumes by the regression model with a 1km resolution.

Fig. 6(b) (right): Harvesting intensity calculated using the predicted local harvesting volumes at 1km scale.

3.3.1 Forest Harvesting Volume

The map of predicted harvesting volumes on a 1km scale (Fig. 6(a), left) generally resembles the overall patterns of the original dataset the statistical model was built upon. There is a clear latitudinal trend which divides the continent into different zones of harvesting volumes: While these are found to be higher in the mid-latitude regions of central Europe and southern Scandinavia, they tend to be lower in southern Europe and northern Scandinavia. However, there are a few exceptions to this trend, especially in southwestern Europe where in ‘hotspots’ of forest use much higher levels of extracted timber volumes per hectare are observed. Namely, these are found in southwestern France in the Landes Forest in the region of Gascony, northwestern Spain (Galicia) as well as northern Portugal. Within these regions, large scale plantations of fast growing species (*Pinus ssp.* in all regions and *Eucalyptus ssp.* on in the Iberian Peninsula) allowed for a significant intensification of forest use [6, 4].

3.3.1 Forest Harvesting Intensity

When the predicted local harvesting volumes are set off against the dataset of regional net annual increment (NAI), an estimate of small scale harvesting intensity and hence sustainability of forest use is gained. The resulting map, shown in Fig. 6(b) (right) reproduces some general trends of the lower resolution original intensity calculations (Fig. 1(b)). Relatively high levels of intensity, possibly indicating unsustainable levels of timber extraction are predicted for regions featuring intensive forestry (e.g. Gascony, Galicia, northern Portugal and northern Italy). However, there also are some considerable differences between the original calculations and the prediction. Especially in northern Scandinavia, high local levels of intensity are predicted. Within these regions, because of climatic conditions very low levels of forest regrowth are prevailing. Thus, timber extraction quickly reaches levels resulting in high harvesting intensity. Moreover, in some regions of southern Europe, especially on the Iberian Peninsula, high levels of harvesting intensity are predicted for multiple relatively small areas. While in the western part of the peninsula (Portugal and Galicia), presumably also because of the introduced fast growing tree species, net annual increment levels are rather high, the other areas of high harvesting intensity in southern Europe (e.g. in central Spain) also fall in regions with low forest ecosystem productivity.

Some of these occurrences of high harvesting intensity are not distinguishable on the original map using the administrative units. These seeming discrepancies can result from multiple factors: On one hand, true regional heterogeneity in forest use as predicted can exist. This for example is expected to be the case in Portugal, where intensive forest use can only be found in the northern part of the country. In fact, the mentioned areas where high levels of harvesting intensity are predicted mostly fall in regions where otherwise low intensity of forest use prevails. Thus, when aggregated on the relatively large spatial units used as reference these small scale patterns of high harvesting intensity can be ‘lost’.

However, on the other hand there are several factors possibly impairing the quality of the local predictions. First, homogeneous levels of net annual increment are assumed for relatively large regions because of the spatial resolution of the dataset available. Second, inaccuracies in the predicted levels of harvesting volume produced by the regression model can lead to corresponding inaccuracies in the levels of harvesting intensity predicted.

As discussed above, absolute measures of model performance (RMSE of 1.74 m^3/ha and R^2 of 0.59) indicate considerable inaccuracies of the statistical model. Thus, to be able to better assess the accuracy of the maps produced, independent validation datasets would be necessary.

4. Discussion and Conclusion

Overall, regression modelling enabled us to produce a high resolution prediction of forest harvesting volume and intensity. The predictor dataset used covered a wide range of possible influence factors that are generally able to statistically describe the patterns of forest use in Europe. While the predictors had a focus mainly on forest structure and environmental conditions, socioeconomic factors might have been underrepresented. The COUNTRY and NAI variables showed by far the highest relative importance, both being very broad variables possibly capturing a wide range of effects. While the NAI variable is strongly linked to different environmental conditions (and therefore other predictor variables in the model) the country dummy was introduced to capture social, politic and structural differences on a nation level.

Even though the model is believed to credibly produce general patterns of local forest use, absolute measures of model performance indicate considerable errors in the prediction produced by the model. Unfortunately no independent test data set was available to assess the quality of the model prediction. Moreover, we assume the quality of predicted local harvesting volumes to be more accurate in countries with smaller administrative units available.

The prediction shows that the patterns of forest use vary significantly across Europe, even at a small spatial scale. There are a few ‘hotspot’ forested areas in Europe where very high harvesting volumes per hectare are predicted. For most parts in Europe the timber extraction does not exceed the ecosystem productivity and therefore implies a sustainable use of forest. However, there is a variety of other factors which are generally considered to be part of sustainable forest use (e.g. biodiversity).

Yet, some regions in the prediction exceed the level of net annual increment and therefore imply a possibly non-sustainable forest use in those areas.

The dataset used in this study is a step in the direction of a Europe wide monitoring of regional forest use. Given the increasing importance of forestry in Europe, more research as well as a more detailed and coordinated collection of data on this topic is an important challenge for the future.

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Tables

Figures