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published in

Forest Ecology and Management
2019

DOI (link to publisher)

[10.1016/j.foreco.2018.10.001](https://doi.org/10.1016/j.foreco.2018.10.001)

document version

Publisher's PDF, also known as Version of record

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citation for published version (APA)

Schulze, K., Malek, Ž., & Verburg, P. H. (2019). Towards better mapping of forest management patterns: A global allocation approach. *Forest Ecology and Management*, 432, 776-785.
<https://doi.org/10.1016/j.foreco.2018.10.001>

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Towards better mapping of forest management patterns: A global allocation approach

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ARTICLE INFO

Keywords:

Global
Forest management
Land use mapping
Global forest resource assessment
FRA 2015
Location factors
Multinomial logit model

ABSTRACT

Forests provide numerous ecosystem services, such as timber yields, biodiversity protection and climate change mitigation. The type of management has an effect on the provision of these services. Often the demands for these services can lead to conflict – wood harvest can negatively impact biodiversity and climate change mitigation capacity. Although forest management differences are important, spatially explicit data is lacking, in particular on a global scale. We present here a first systematic approach which integrates existing data to map forest management globally through downscaling national and subnational forest data. In our forest management classification, we distinguished between two levels of forest management, with three categories each. Level 1 comprised primary, naturally regrown and planted forests. Level 2 distinguished between different forest uses. We gathered documented locations, where these forest categories were observed, from the literature and a database on ecological diversity. We then performed multinomial logit regression and estimated the effect of 21 socio-economic and bio-physical predictor variables on the occurrence of a forest category. Model results on significance and effect direction of predictor variables were in line with findings of previous studies. Soil and environmental properties, forest conditions and accessibility are important determinants of the occurrence of forest management types. Based on the model results, likelihood maps were calculated and used to spatially allocate national extents of level 1 and level 2 forest categories. When compared to previous studies, our maps showed higher agreement than random samples. Deviations between observed and predicted plantation locations were mostly below 10 km. Our map provides an estimation of global forest management patterns, enhancing previous methodologies and making the best use of data available. Next to having multiple applications, for example within global conservation planning or climate change mitigation analyses, it visualizes the currently available data on forest management on a global level.

1. Introduction

Forests provide numerous ecosystem services, such as carbon sequestration, biodiversity conservation, water regulation, erosion control, habitat, recreation space and many more (Ninan and Inoue, 2013). Probably the most prominent is the production of wood biomass, one of the crucial resources for humankind. Our dependence and needs for a wide range of forest ecosystem services is reflected in different types of forest management. These either aim for maximizing the provision of one service (usually timber production) or compromise between several services. However, they can also result in different levels of pressures, alteration and degradation of forests. A distinction can be made between so-called “conventional” and “alternative” forest management. Conventional practices aim for an increase of timber yields and harvest

efficiency, usually resulting in species-poor and even-aged forest stands (Puettmann et al., 2015). Alternative silvicultural systems are aiming for more diversity in age, species and structure (Puettmann et al., 2015).

Globally, there are different ways of how these types are implemented. For Europe, Duncker et al. (2012a) classified five different forest management approaches, ranging from passive (unmanaged forests) to intensive (short-rotation forests). The two approaches with the highest management intensity (i.e. high and intensive) thereby correspond to conventional silviculture and the once with lower management intensity, i.e. low and medium, describe alternative systems. In the tropics, selective logging is a common practice for both, conventional and alternative logging systems, since natural forests have a high variety of tree species and only some are suitable for timber

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<https://doi.org/10.1016/j.foreco.2018.10.001>

Received 22 March 2018; Received in revised form 28 August 2018; Accepted 1 October 2018

Available online 12 October 2018

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(Chaudhary et al., 2016). Therefore, a distinction is made between conventional selective logging with heavy machinery and reduced impact logging, which includes harvest planning and practices that cause less damage (Puettmann et al., 2015).

In general, high management intensities result in high merchantable timber yields and can be beneficial for climate change mitigation (Duncker et al., 2012b). However, when large trees are harvested unsustainably, smaller trees can get damaged or destroyed, which can significantly contribute to carbon loss and forest degradation (Martin et al., 2015). High management intensity also negatively affects other ecosystem services (Duncker et al., 2012b; Pukkala, 2016), for example biodiversity. The magnitude of the effect on biodiversity varies substantially among management type, geographical location and affected taxonomic group (Chaudhary et al., 2016). Logging can result in a high age class diversity, when conducted at low historical rate or maximum age, thereby mimicking a natural disturbance regime (Colombo et al., 2012). On the other hand, logging is, besides crop farming, the biggest threat to Red List species (Maxwell et al., 2016). Wood production and trade were furthermore identified to contribute substantially to extinction risks of bird species (Nishijima et al., 2016). Moreover, the conversion of a forest to a timber plantation can have an effect on species composition and is one of the main drivers of extinction and biodiversity loss (Newbold et al., 2015).

Demands for forest ecosystem services, particularly wood, will likely increase in the future, due to demographic changes, economic growth and the encouraged use of biomass for energy production (Egnell et al., 2011; FAO, 2009, 2016). Additional pressure on forests can be expected from expanding agricultural areas to fulfill the global food demand (Lambin and Meyfroidt, 2011) and an increase of land demands for biodiversity protection and climate change mitigation (Eitelberg et al., 2016). To analyze future impacts of land use conversions, land change models are often applied, driven by human demands for food, resources and living space (Brown et al., 2013; Veldkamp and Lambin, 2001). In such models, forest is often classified based on the land cover only. The same is valid for conservation planning through the identification of priority areas, where forests are included only in terms of forest cover (Brooks et al., 2006). Habitat loss due to forest degradation or conversion to monoculture plantations is, consequently, not considered. To estimate an area's relative importance for biodiversity protection or its contribution to climate change mitigation, it is necessary to go beyond forest cover and deforestation patterns. There is a need to better consider the spatial patterns of forest management.

Several datasets exist that give information of forest management types. On a national scale, there is the Global Forest Resources Assessment (FRA), compiled by the Food and Agriculture Organization of the United Nations (FAO). It provides an insight into characteristics and functions by giving extents of different forest categories, gathered from national inventories, partially using remote sensing (MacDicken, 2015). On a spatial explicit level, some previous studies aimed to capture patterns of different forest management on national, continental or global scales (Hengeveld et al., 2012; Hurtt et al., 2011; Kraxner et al., 2017; McGrath et al., 2015; Naudts et al., 2016; Petersen et al., 2016; Verkerk et al., 2015). Three reoccurring main approaches were found in the literature: (1) an evidence-based approach, (2) reconstruction of historical wood harvest and land use and (3) direct observation through remote sensing. Although these existing efforts have resulted in different maps, they are either spatially restricted, are based on rather simplified assumptions or use a coarse thematic resolution (see SI for a more in-depth inventory).

A systematic approach of identifying global patterns of forest management is still missing. The objective of this study is therefore to improve our understanding of global forest management types. We aim to map forest classes, such as natural or planted forest and forest uses, such as for production. While these are not equal to forest management systems, they give information on where wood is produced and where forests are disturbed by humans. Moreover, we aim to study the

Fig. 1. Simplified flowchart of the methodology. The flowchart depicts inputs (left), process steps (middle) and interim results (right) for the creation of global forest management maps. The colors indicate which part of the method section a thorough explanation can be found - orange: *Classes and data*, dark blue: *Preparation for spatial analysis*, turquoise: *Likelihood maps and allocation*.

underlying drivers behind the location of different forest classes and uses, by integrating publicly available global data and build up on the methods currently used in the literature.

2. Methods

The following paragraph gives a brief overview of the methodology. Each step is then explained in more detail in the following sections. Our methodology is based on downscaling national and subnational data using empirical data to determine the likelihood of finding a forest management type at a specific location (see Fig. 1), following the method applied in previous studies (Kraxner et al., 2017; Verkerk et al., 2015). We determined the likelihood of finding a specific forest management type by estimating multinomial logit regression models. This included evaluating the effect of 21 different predictor variables. For the dependent variable, data points from the literature and a new database of case study observations on ecological diversity were used. Hypotheses on the behavior of predictors were made beforehand. By means of significance and effect of predictors, we calculated likelihood maps for the occurrence of different forest categories. Those formed the basis of spatial allocation of forest classes. Our final maps represent an estimation of two levels of global forest management patterns for 2000 at a 1 x 1 km² resolution, following an underlying forest cover map (see below).

2.1. Classes and data

We used national forest data from FAO's FRA, 2015 version (FAO, 2016) for the year 2000. The FRA is a data collection of the extents of different forest categories for in principal all countries and territories, but for some countries data is missing or these countries do not have any forest cover (Table S.4). An important advantage of the FRA dataset is its global coverage and given definitions. Furthermore, it is commonly used in land and global change studies, e.g. on climate change, biodiversity and remote sensing, substantially contributing to more than 150 studies (Grainger, 2008). The FRA dataset was improved with subnational statistics, thereby increasing the spatial resolution of information for the seven biggest countries, namely Australia, Brazil, Canada, China, India, Russia and the USA (see Table S.1 for data

sources). This comprised for all seven countries subdivision extents on production and plantation forests. For Brazil, Russia and the USA extents for primary forests were additionally included. In Russia, this was done by using mature and over-mature forest extents as a proxy.

For Brazil, we used the biome-wide extents from the FRA country report. In the USA, we used the share of “Reserved forests” as a proxy for Primary forests in Alaska (46%) (Oswalt et al., 2014). To keep the differences in time and definitions as small as possible, subnational data was adjusted to the corresponding FRA values by using relative distributions across the subnational units.

The relations between forest management and location factors were estimated with help of spatial explicit point information. The biggest share of these points came from the Projecting Responses of Ecological Diversity In Changing Terrestrial Systems (PREDICTS) database (Hudson et al., 2014). This dataset comprises biodiversity factors and the relationship to anthropogenic land use pressures. Each data entry includes inter alia geographical coordinates, the predominant habitat category and an informal description of the habitat. We used the latter two for the classification of points. Most of the points are clearly defined to be located within a forested area, such as by the predominant habitat category “plantation forest” or “high-intensity logging” as a description of the habitat. For some points, it was uncertain if the habitat actually describes a forest, e.g. terms like “regrowth”, “revegetation”, “ancient forest” or “abandoned field” of “mature vegetation”. Those points were included if they were located within the delineated forest area. Additionally, point information was collected from the literature following the reference list from Chaudhary et al. (2016) and Paillet et al. (2010).

After interpretation of forest descriptions and FRA categories, we identified two levels with each three forest categories: Level 1, hereafter also called forest classes, comprised (1) primary, (2) naturally regrown and (3) planted forests. For level 2 of our classification, we included different forest uses, namely: (1) forests primarily used for production, (2) forests used for multiple purposes and (3) forest primarily used for other purposes (e.g. recreation or protection). The two levels are co-existent, while the categories of each level are considered to be mutually exclusive, according to their FRA definitions (MacDicken, 2012), and constitute the entire forest extent. An exception formed Finland. Here, the sum of the extent for production forests and forests used for multiple purposes was larger than the entire forest extent. Both extents were exactly equal. We assumed that due to the Finnish forest legislation and the everyman’s right, production forests were also classified as forests used for multiple purposes. The FRA definition of Multiple Use forests states that forests should not be classified as multiple use due to general legislations or clauses (MacDicken, 2012). Therefore, we decided to only consider the extent as forests, primarily used for production and ignore the extent for multiple use.

Sufficient data points for forests used for multiple purposes were lacking and could therefore not be included in the model. A big share of naturally regrown forests in the PREDICTS database is related to abandoned - mostly former agricultural - areas. We assumed that these areas differ substantially from currently used and never used areas. Therefore, abandoned areas were included as a category for the dependent variable of level 2 forest categories to improve the model fit. This sub-category, however, was not spatially assigned, since its national extents are not included in the FRA dataset.

To minimize pseudo-replication and due to our intended spatial resolution of $1 \times 1 \text{ km}^2$, the included points had to be at least 1 km away from each other. If more than one forest category was reported within this radius, we included the one with the highest management intensity (i.e. plantation before naturally regrown before primary forest and production before multiple uses before no/other use). Altogether, we had 789 observations available (see Fig. S_2).

2.2. Preparation for spatial analysis

A global binary forest mask (forest/no forest) formed the spatial restrictive base layer for all following spatial analysis. We adjusted the forest hybrid raster layer by Schepaschenko et al. (2015) with forest extent values of the year 2000 from the FRA 2015 version (see SI for more details). The forest mask, and all other spatial layers mentioned hereafter, were transformed to Eckert IV – a pseudocylindrical, equal-area projection (Snyder and Voxland, 1994), commonly used and one of the most preferred by the cartographers and map readers (Šavrič et al., 2015).

Global forest areas were divided into 4 regions, based on terrestrial biomes (Olson et al., 2001): (1) Tropical and subtropical forests, (2) Temperate and Mediterranean vegetation, (3) Boreal vegetation and (4) Tropical and subtropical wood- and grasslands. The separation was conducted on a country level, classifying a country according to the biome that is predominately covering its forest. In 12 countries (see SI), none of the four selected biome groups occurred in the forested area. In these cases, every forest pixel within the country got reassigned according to the one of the 4 biome groups that was in the closest vicinity. The biome with the biggest share within the newly assigned pixels determined in which group the country was classified (see Fig. S_1).

2.3. Likelihood maps and allocation

For downscaling the national and subnational data, we took into consideration a total of 21 possible predictor variables or location factors (see Table 1) of different groups: accessibility, governance, soil, climate and terrain conditions and forest properties. The choice of predictor variables built on findings of previous studies and spatial availability on a global scale. Some variables that showed significance in region-wide forest management, for instance tree species distribution (Levers et al., 2014; Petersen et al., 2016), were left out due to missing global spatial data. We refined some location characteristics, for instance soil properties included eight different variables, instead of using solely an indicator for poor soils as it was done in previous studies (Levers et al., 2014). We aimed to use the most suitable dataset for predictor variables.

This meant that sometimes we choose consistency over actuality, e.g. the underlying road map was chosen since the data was compiled from a single year with a consistent methodology. (Dubinin, 2014). Some variables were additionally tested in a truncated or relativized (difference from optimum) form to account for potential non-linear responses. A thorough elaboration on these modifications, a rationale for choosing the variables and its expected cause and/or influence is given in the SI (Table S_1). To predict the likelihood of forest classes and uses, we used a multinomial logit model. This is similar to logistic regression but with a categorical dependent variable. Logistic regression is commonly used for the identification of drivers for decision making and land use analysis (Ludeke et al., 1990; RUTHERFORD et al., 2007; van Asselen and Verburg, 2012). Advantages of this type of regression include the discrete outcome, appropriate for probabilities and smaller requirements for the independent variables, i.e. data does not have to be normal distributed or scaled. Modelling was conducted in R (R Core Team, 2016), using the multinom algorithm from the nnet package (Venables and Ripley, 2002). A step-wise model reduction was applied by excluding those variables that are increasing the Akaike Information Criterion value (Snipes and Taylor, 2014). To estimate the final model fit, we calculated the receiver operating characteristic curve and the area under this curve, both with functions from the pROC package (Robin et al., 2011). Besides the original forest categories, we estimated if combining sub-categories would increase model performance, i.e. combining primary and naturally regrown forests to ‘natural forests’, no use and abandoned to ‘not currently used forests’ or abandoned and production forests to ‘historically or currently used forests’.

Likelihood maps in form of $1 \times 1 \text{ km}^2$ raster layers were calculated

Table 1

Predictor variables for modelling likelihoods for the occurrence of naturally regrown, plantation and production forests.

Predictor	Description	Unit	Source
NPP	Net Primary Productivity	Units of elemental C	Imhoff et al. (2004)
Tree density	Percentage tree cover	%	ISCGM (2008)
Forest loss	Forest change between 2000 and 2014, aggregated with summation	binary	Hansen et al. (2013)
Forest gain	Forest change between 2000 and 2014, aggregated with summation	binary	Hansen et al. (2013)
Elevation	Altitude in meters above average sea level	m	GTOPO30: USGS EROS (1996)
Slope	Derived from elevation map	%	Own calculation
Sand content	Share of sand in soil texture	%	S-World: Stoorvogel et al. (2017)
Clay content	Share of clay in soil texture	%	S-World: Stoorvogel et al. (2017)
Soil depth	Total depth of the soil	cm	S-World: Stoorvogel et al. (2017)
Depth of topsoil	Depth of the topsoil layer	cm	S-World: Stoorvogel et al. (2017)
C content in subsoil	Carbon content in the subsoil layer	%	S-World: Stoorvogel et al. (2017)
C content in top 50 cm	Carbon content in the layers of the top 50 cm of the soil	%	S-World: Stoorvogel et al. (2017)
C content in topsoil	Carbon content in the topsoil layer	%	S-World: Stoorvogel et al. (2017)
Drainage classes	Soil drainage differentiating between 7 different classes from 1: Very poorly drained to 7: Excessively drained	Categorical	WISE30: Hengl et al. (2014)
Aridity Index	Ratio between average yearly precipitation and average yearly potential evapotranspiration.	No unit	CGIAR-CSI Global-Aridity and Global-PET Database: Zomer et al. (2007); Zomer et al. (2008)
Market accessibility	Distance and travel time to international and regional markets	No unit	Verburg et al. (2011)
Travel time to major cities	Accessibility measured in travel time to cities with > 50.000 inhabitants	hours	Uchida and Nelson (2009); Uchida and Nelson (2010)
Distance to roads	Euclidian distance to roads calculated based on the most consistent global road map	km	Dubinin (2014)
Distance to rivers	Euclidian distance to rivers	km	Pape (2004)
Population density 2015	Population density, downscaled with urban built-up areas	People/km ²	Freire and Pesaresi (2015)
Aggregated governance index	Determines perception of governance within a country. Aggregation by sum of 4 indices: regulatory quality, government effectiveness, control of corruption and rule of law	No unit	Kaufmann and Kraay (2017)

by means of model outcomes and used for the allocation of forest classes and uses. For countries where all three forest classes of level 1 were reported, we used a numerical allocation algorithm. Forest classes were first assigned according to the relative highest likelihood value (i.e., the forest management type with the highest likelihood at a location is allocated). The allocated areas were then compared with the extent given in the data. If the allocated extent was too small or too big, the values of each pixel of the likelihood maps for that specific forest class were increased or decreased, respectively. The procedure was done until the values given in the FRA/subnational data were met. This allocation procedure was implemented with a modified version of the Dyna-CLUE model, which has this algorithm embedded in the software (Verburg and Overmars, 2009).

For countries, where primary forest and only one other forest class was reported (i.e. without either naturally regrown forests or planted forests), a simple allocation procedure was used. In this case, the highest values in suitable areas were assigned to the respective class until the extent given in the FRA was fulfilled. The remaining areas were classified as primary forest. The allocation of forest uses followed a similar procedure. First production forests were allocated to areas with highest production suitability until the given extent was met. Due to the lack of data points for multiple use forests and hence a suitability map, production likelihood was also utilized for the allocation of this forest use type: Areas not assigned as production forests with the highest likelihood values were classified as forests used for multiple purposes until the given extent was met. This followed the rational that timber harvest is often an important part of forests used for multiple purposes but is usually done in a less intensive manner than in production forests (Horne et al., 2005). The remaining areas were classified as used for primarily other purposes (other/no use).

We tested the difference between the numerical allocation algorithm and a simple hierarchical approach. In the hierarchical algorithm, plantations were allocated first, followed by naturally regrown forests and the remainder of the forest area was classified as primary forests.

For planted and production forests, areas of intact forest landscapes (Potapov et al., 2008) were excluded from the allocation procedure. Likelihoods for planted forests within protected areas of any category by the International Union for Conservation of Nature (IUCN) (IUCN and UNEP-WCMC, 2015) were rescaled to values below the minimum value of the map by subtracting the range of likelihood values. The same was done for production forests within protected areas of the categories Ia, Ib, and II. This ensures that these protected areas are only considered if no other location is possible. These exclusions followed the IUCN definitions (Dudley and Phillips, 2006) but violation of the premise has been reported (see e.g. Peter and Pheap, 2015 for Cambodia) and logging is an important threat to many protected areas (Schulze et al., 2018).

2.4. Comparison with other studies

No comparable global dataset on forest classes and uses exists so far. The spatial global distributions of plantations, naturally regrown and primary forests, or forest used for production or multiple purposes are therefore unknown. We cross-validated our maps with different existing datasets.

First, we collected 47 additional data points within literature from 2015 to 2017 in Web of Science (www.webofknowledge.com) using the same search query like Chaudhary et al. (2016) (see SI). Those points were classified as planted or not planted forests for level 1 classes. For level 2, areas used for production were identified. A finer classification,

i.e. including primary and naturally regrown, or multiple use and other use forests, was not possible, since the interpretation of the descriptions given in the literature was too uncertain. We evaluated how far planted and non-planted forest points are away from planted areas classified in our map and compared the distances. Additionally, we assessed the distance between timber logged points from the literature and the predicted areas of production forest in our map and compared them to a random sample.

Second, the location of unmanaged forests, part of the global map of certified forests (Kraxner et al., 2017) was compared to predicted locations level 1 forest classes in our map. We assumed that unmanaged forests should be mostly primary forests and were not planted. Third, predicted plantations were compared with a map of plantations in selected tropical countries based on remote sensing interpretation (Petersen et al., 2016). Only rubber and timber plantations were thereby considered, since all other (i.e. fruit, palm and unknown) are not included in the planted forests extents in the FRA. Because of that, no plantations in Colombia and Liberia were included. Furthermore, rubber plantations in Indonesia were excluded, since they are not part in this country's FRA data (FAO, 2014). We then calculated the distance of the locations in the plantation dataset to the nearest predicted plantation in our map. To estimate the performance, we compared this result to two random samples in the countries under consideration. One sample consisted of random locations within the countries' terrestrial area, the other within the countries' forest area.

Fourth, we compared the trends of wood production in European forest (Verkerk et al., 2015) between our forest categories. Fifth and last, we checked for agreement of our map with the European forest management types mapped by Hengeveld et al. (2012). To do so, we assumed that even aged and short rotation forestry correspond with our class of forest primarily used for production. Combined objective forestry was assumed to equal to forests used for multiple purposes. Nature Reserve and Close-to-Nature Management describe forests used primarily for other functions.

3. Results

3.1. Predictors of forest management

Significant predictors for the forest categories, as well as their estimated effects are presented in Table 2. Summarizing, we found that even though significant predictors are different for the different world regions, variables from all groups were significant. For all regions, the likelihood of timber production increased in more arid areas (Table 2). This might seem contradictory to the previously investigated positive relationship between precipitation and forest productivity in Europe (Levers et al., 2014; Verkerk et al., 2015). However excessive humidity can cause soil erosion especially when timber is harvested through clear-cutting or similar techniques that are creating openings in the crown cover. Moreover, high precipitation is mostly found in higher mountain ranges and areas of difficult accessibility. More humid conditions increased the likelihood of naturally regrown forests in the tropics and subtropics and abandoned areas in tropical and subtropical forests. A possible explanation for this relation is the use of shifting cultivation which occurs in large areas in the humid tropics (Heinimann et al., 2017). Similarly to results of a previous study (Banin et al., 2014), likelihoods for plantation and timber production forests in tropical forests were increased by better soil conditions, in particular deeper, soils with higher carbon contents and less excessive drainage. The better growing conditions were also reflected in higher NPP. For the other biomes, soil conditions were less determining. Previous studies have found that terrain ruggedness and slopes reduce harvest intensities in Europe (Levers et al., 2014; Verkerk et al., 2015). Our results show the same relationship for production forests in the tropics but no significance for the temperate zone. Furthermore, an opposite effect occurred in production forests of tropical and subtropical grasslands. Our

study potentially missed the impact of local steep slopes, due to the derivation of slope data from a 1 x 1 km² evaluation map. Variables describing accessibility were significant for naturally regrown and plantation forests of all biomes and for production forests of all biomes, but temperate forests. Forests used for timber harvest are usually more apart from cities due to e.g. fumes from paper and pulp mills, negative impacts of infrastructure and demand for other functions of forests closer to cities, such as recreation (Verkerk et al. 2015). In the temperate zone, where proximity between cities is usually rather high, this results in the observed positive effect of travel time. In the tropical and boreal forest, however, areas can be much more remote and inaccessible, leading to a negative effect of remoteness, in particular for planted forests. When significant, tree cover was lower for naturally regrown, planted and production forests, compared to more undisturbed forests systems, contrary to findings of Levers et al. (2014) and the assumptions of Hengeveld et al. (2012). Coupled with the observed positive relationships of forest loss, this implies that even though a forest with a higher tree cover might be chosen for wood production, the degrading effect of harvest on a forest is more prevalent.

The area under the curve, a measure of the receiver operating characteristic curve, was in general high with values between 0.8 and 1.0 (see Table 2), suggesting a good model fit. For some categories, it even reached 1.0. However, this was likely related to the limited amount of forest data points available for some biome - forest class or use combinations.

The combination of forest classes (e.g. to natural forests) and the combination of forest uses (e.g. historical and current use) did not achieve a better model fit than the original categories (see Table S.5). Likelihood raster maps, calculated by means of the regression results, formed the basis for the allocation of forest categories. When comparing the applied allocation algorithm with a hierarchical one, we found that especially the location of planted forest was affected. In each biome, approximately half of plantations did get located in a different position. For the other forest classes, differences were smaller. The final level 1 and level 2 maps can be found in Figs. 2 and 3, respectively.

3.2. Comparison with other datasets

We compared the distance of 47 data points, additionally collected from the literature between 2015 and 2017, to plantations mapped in our study. We found that with an exception of two points, all plantation forests from the literature were 10 km or less away from predicted plantations and about three-quarter were within a radius of 5 km. Non-planted forests were more often further away. We identified in total 31 data points on timber logged forests from the literature. More than two-thirds of the points were 5 km or less away from areas classified as production forests in our maps and ca. 75% of the points were within 10 km distance from production forests. Distances between random samples and mapped production forests were in general larger (Fig. S.4).

Additionally, the calculated maps were compared with previously published maps of forest management or characteristics. We evaluated the location of planted and production forests within managed and unmanaged forests, delineated by Kraxner et al. (2017). Compared to managed forests, unmanaged forests contained less plantation and production forest (Fig. S.5). In particular, planted forests constituted 2% of the area of unmanaged forests and production forests 24%. In managed forests, those types accounted for 5% and 28%, respectively. Additionally, the share of primary forest was bigger in unmanaged forest (47%) than in managed forests (34%).

The distance of locations of plantations based on an existing plantation dataset (Petersen et al., 2016) was compared to the nearest plantation in our prediction. More than half (56%) were located 10 km or less from our predicted ones and only about 7% were further away than 50 km (Fig. S.6). In South-East Asia, even 70% are within 10 km and almost all within a 50 km radius. The total size of plantations that

Table 2

Results of the multinomial logit regression models on significance (* indicates a $p < 0.01$ and * a $p < 0.05$). The reference level of the dependent variable for level 1 was primary forest and for level 2 it was no/other use forest.

Level 1		(Sub-) Tropical forests		Temperate vegetation		Boreal forests		(Sub-) Tropical grassland	
Variable		Naturally regrown	Plantation	Naturally regrown	Plantation	Naturally regrown	Plantation	Naturally regrown	Plantation
(Intercept)		−2.1*	−6.9·10 ^{−1} *	−6.2*	−2.2	−4.3·10*	−1.0·10*	−3.7·10*	1.4·10 ³ *
Travel time to cities		6.2·10 ^{−4} *	−8.9·10 ^{−5}	2.8·10 ³	5.4·10 ³ *	1.1·10 ² *	−4.9·10*		
Market access index				1.0·10*	8.1*				
Trunc. market index								6.3·10 ² *	−2.4·10 ² *
Distance to roads		2.4·10 ^{−5} *	−4.0·10 ^{−5} *			−4.8·10 ^{−4} *	2.0·10 ³ *		
Population density		−9.9·10 ^{−4}	7.3·10 ³						
Trunc. population density				1.6·10 ^{−2}	3.5·10 ^{−2}				
Aggr. governance index				2.8*	−1.4*	8.5*	−3.8·10*		
Forest gain				1.3·10 ^{−2}	5.6·10 ^{−2} *				
Forest loss		2.5·10 ^{−3}	3.9·10 ^{−3} *						
Sum loss and gain								−2.7	−2.0*
% tree cover		−9.0·10 ^{−3}	−5.7·10 ^{−2} *					−4.8	−6.1*
Elevation			−6.8·10 ^{−3}	−4.6·10 ^{−3} *				−4.2·10 ^{−1} *	−1.3*
Slope								4.2·10 ^{−2}	4.1·10*
Aridity index		7.1·10 ^{−1} *	−3.4*	−1.2·10*	5.2*	−1.7·10*	−8.9·10 ^{−1} *	9.9·10 ² *	1.1·10 ³ *
2		−1.6*	1.3·10*					−3.3·10*	1.3·10 ² *
Drainage class		−8.5·10 ^{−1} *	4.1·10 ^{−1} *						
3		1.0*	−1.0*					2.1·10 ² *	−2.0·10 ² *
(Ref: 4)		−9.7·10 ^{−1} *	−2.3*					2.6·10*	−4.1·10 ² *
5		−1.5·10*	−2.3·10*						
6		5.9·10 ^{−2} *	−6.2·10 ^{−2}					−5.3*	−1.8·10*
7		−7.3·10 ^{−3}	6.0·10 ^{−2} *						
Depth topsoil		−1.2·10 ^{−2}	3.6·10 ^{−2} *					−9.2	5.2*
Soil depth				1.1·10 ^{−1}	6.8·10 ^{−2}	−4.9·10 ^{−1} *	3.2·10 ^{−1} *	2.1·10*	2.9·10*
Trunc. topsoil carbon									
Relative clay content		−2.0·10 ^{−2}	7.2·10 ^{−2} *						
Relative sand content		−2.7·10 ^{−2} *	7.1·10 ^{−2} *	−7.4·10 ^{−2}	−5.9·10 ^{−2}	5.3·10 ^{−1} *	2.7·10*	−9.8*	−3.0·10*
Net primary production									
AUC		0.890	0.940	0.779	0.986	0.987	1.000	1.000	1.000

Level 2		(Sub-) Tropical forests		Temperate vegetation		Boreal forests		(Sub-) Tropical grassland	
Variable		Abandoned	Production	Abandoned	Production	Abandoned	Production	Abandoned	Production
(Intercept)		−2.9·10 ^{−1} *	−1.1*	6.4·10*	−2.3	1.4*	4.6·10*	−1.3·10 ³	2.3·10 ³
Market access index		2.9*	−3.8·10 ^{−1} *					−1.9·10 ³ *	−1.2·10 ³ *
Distance to roads		6.7·10 ^{−5} *	2.4·10 ^{−5} *			−1.6·10 ^{−4} *	−2.5·10 ^{−4} *	2.4·10 ^{−1}	9.9·10 ^{−2} *
Population density		1.9·10 ^{−3}	6.5·10 ^{−3} *						
Aggr. governance index		1.3·10 ^{−2} *	2.3·10 ^{−1} *	4.4·10*	1.1*				
Forest gain								−8.1·10 ^{−1}	−1.5
Forest loss		3.9·10 ^{−3} *	2.6·10 ^{−3} *					−1.6·10	1.1·10
Sum loss and gain				−3.6·10 ^{−1} *	1.1·10 ^{−1} *				
Net gain				2.7·10 ^{−1} *	−8.4·10 ^{−2}				
% tree cover		−2.9·10 ^{−2} *	−6.5·10 ^{−2} *						
Elevation				−1.9·10 ^{−1} *	4.0·10 ^{−3}				
Slope		−2.1·10 ^{−1} *	−1.3·10 ^{−1} *					2.2·10*	3.7·10
Aridity index		1.4*	−1.3*	−4.4·10*	−3.8*	2.9·10*	−7.8*		
1						−2.4*	1.0·10*		
2		4.2·10 ^{−1} *	1.5·10*			1.4*	9.0*	−1.5·10 ² *	1.2·10 ³ *
Drainage class		−4.3*	1.3·10*						
3		4.2·10 ^{−1} *	1.0*			2.5*	1.9·10*	−1.7·10 ³ *	−4.6·10
(Ref: 4)		−1.4*	−1.8*			1.5·10*	7.2*	3.4·10 ² *	1.4·10 ³ *
5		−2.0·10*	−3.6*			−1.3·10*	1.1·10*		
6		7.3·10 ^{−2} *	7.5·10 ^{−3}						
7		6.1·10 ^{−3}	6.1·10 ^{−2} *	−2.6*	3.9·10 ^{−2}	−2.6·10 ^{−1} *	−3.1·10 ^{−1} *	−5.9	−1.2·10
Depth topsoil		2.0·10 ^{−2}	3.2·10 ^{−2} *						
Soil depth		−9.2·10 ^{−2} *	−4.9·10 ^{−2} *						
Topsoil carbon content									
Clay content									
Relative clay content								1.4·10 ² *	5.1·10*
Sand content						−2.9·10 ^{−1} *	−2.6·10 ^{−1} *	−5.3·10*	−4.2·10*
Relative sand content				−2.0*	−1.4·10 ^{−1}				
Net primary production		−4.4·10 ^{−2} *	4.7·10 ^{−2} *			−9.2·10 ^{−1} *	4.6·10 ^{−1} *	4.7·10*	−1.2·10
AUC		0.932	0.866	1.000	0.967	0.961	0.967	1.000	1.000

+: $p < 0.01$; *: $p < 0.05$; Trunc.: Truncated; Aggr.: Aggregated; Ref: Reference level.

were mapped by Petersen et al. exceeded FRA statistics for Brazil (1.5 times more), Cambodia (9 times more) and Indonesia (3.5 times more). In Malaysia and Peru, the mapped areas were smaller than the FRA data (33% of the FRA data and 0.5%, respectively). Random locations were considerably more distant from the plantations in the Petersen dataset than predicted plantations (Fig. S_6).

The wood production in European forests (Verkerk et al., 2015) was

on average higher in areas predicted to be planted, compared to naturally regrown forests and lowest in primary forests. A similar trend was found for level 2 forest management types. Predicted production forests had on average higher wood production values, compared to multiple and other uses (Fig. S_7). Lastly, our map showed in 30% of the locations an agreement with respective forest management classes mapped by Hengeveld et al. (2012) in European forests (Fig. S_8).

Fig. 2. Global patterns of forest classes for the year 2000. The map shows the distribution of primary, naturally regrown and planted forest. The original dataset in a $1 \times 1 \text{ km}^2$ resolution is available at: www.environmentalgeography.nl.

4. Discussion

Our study is the first global map that allocates three different forest classes and three different forest uses. We thereby provide a finer thematic resolution than any existing global forest management map. We increased the information from the FRA data by including subnational data for the seven biggest countries. Specificity was enhanced by estimating the effects and significance separately for 4 world regions rather than making global generalizations. Furthermore, relationships between forest management and location characteristics were determined empirically, thus going beyond expert-based estimates. Global maps from previous studies based the spatial allocation of forest management types solely on indicators of human use (Hurt et al., 2011; Kraxner

et al., 2017). Our results show that variables of human impact play an important role for the location of forest classes and uses. But we found that soil or climate properties and forest conditions are having an important influence, too. These findings are similar to a previous study of drivers of forest harvest in Europe (Levers et al., 2014) and make clear that forest management cannot be predicted based on a single indicator.

Most of the results on significance and effect direction of predictors are supporting the findings of previous studies. Some give us new information on indicators of forest management classes. Examples are the negative relationship of tree density to the likelihood of a forest with more disturbances (i.e. naturally regrown, planted or production forests) or the increased likelihood for production forests in more arid areas of the tropics. One national variable was included as predictor: an

Fig. 3. Global patterns of forest uses for the year 2000. The map shows the distribution of forest used for production, multiple purposes or primarily for something else than production (other). The original dataset in a $1 \times 1 \text{ km}^2$ is available at: www.environmentalgeography.nl.

aggregated governance index. While it does not affect the allocation of forest classes, its significance supports the importance of country specifics, which has been reported before for forest management in European countries (Levers et al., 2014).

But not every relationship corresponds with the stated hypotheses. In the tropics, the likelihood for production forests increased with the distance to roads. This could be misinterpreted as very remote forest areas without infrastructure being more likely used for production, contradicting to the link between accessibility and wood harvest (Kleinschroth and Healey, 2017). While being consistent in time and methodology, the roadmap of our choice did not include smaller roads. Hence the relationship refers to the bigger road network. Rivers are a common transporting way of timber logs in tropical forests, especially in areas that are hard to access. To account for the rather low coverage of roads especially in the tropics, the distance to rivers was tested as well. There was a significant relationship when tested in univariate models, but it did not increase the model quality (measured with the Akaike Information Criteria) of the multivariable models and hence it was not included. We refrained from using a threshold for remoteness (Levers et al., 2014), since it would largely depend on the country and region and would affect the consistency of our methodology.

The high AUC values for our model are a sign for a good model fit and the derived likelihood maps can be considered to be relatively accurate. When cross-validating our maps with several different previous datasets, they performed better than random samples and often matched within a distance of 10 km. The mapped area of planted forest was thereby more similar to the external data than the maps for production forests.

Despite the given definitions and the strive to create a consistent dataset, the FRA bears uncertainties, due to errors in national inventories, projection errors and/or aggregation of classes (Grainger, 2008). The provided tier system can give an indication of the reliability of the data source. However, more sophisticated measurement methods (and hence a higher tier) does not necessarily provide higher accuracy (Hill et al., 2013). We, therefore, did not include the tiers as a measure of accuracy of the data or our map. Adding to the existing uncertainties in the FRA, several assumptions were made for countries where data was missing, to minimize data gaps in our maps. All these inconsistencies lead to country effects, as they occur for example at the borders between Colombia, Brazil, and Peru. Even though the FAO made an effort to reduce the reporting burden, the previously observed differences of monitoring capacity between countries (Furukawa et al., 2015) seem still existent. Furthermore, forest classes and uses seem to not always be understood the same way, even though they have a relatively clear definition. For instance, primary forests are defined as forests without “clearly visible indications of human activities” (MacDicken, 2012, p. 7). Hence, primary forest areas should not be intensively used for production. However, for nine countries the reported extents for both sub-categories were so large, that they had to overlap. For planted forests, it is often not clear which type of plantations are considered within the data. The huge and inconsistent differences between the amounts mapped by Petersen et al. (2016) and the given FRA data emphasize this issue. However, when the distribution of plantations predicted in this study and mapped by Petersen et al. (2016) were compared in the Malaysian peninsular (the only validated region within their dataset) patterns show similarity (see Fig. 4). Furthermore, monitoring of the extent of forests used for multiple purposes and the distinction to production forests seems to be a problem. In Finland, the extents for production and for forests used for multiple purposes were for both so large, that they would need to overlap within the given forest area, even though their definitions imply that they cannot coexist at the same place. Additionally, 19 countries do report all their forests as forests used for multiple purposes and about 29 countries do report level 1 forest management classes, but neither production nor multiple use forests. These are probably the reasons, why level 2 forest management types show bigger differences to maps from other studies than

Fig. 4. Comparison between mapping approaches on the Peninsular of Malaysia. The picture shows that there are the differences and similarities of our approach with the mapping by Petersen et al. (2016). While patterns are similar, the amounts of mapped plantations are not equal and some mapped areas by Petersen et al. occur outside of our designated forest cover.

plantations do. Our map visualizes these data problems and will hopefully contribute to more attention for solving these inventory and reporting issues. We excluded protected areas of IUCN class I to III, even though illegal logging in protected areas has been reported in many countries (Kleinschmit et al., 2016). This may lead to deviations of our map with the reality but consistent and comprehensive data on the extent of illegal activities is not available. Another limitation of our study is the point data on forest management, which formed the base of the relation estimation of location factors. The locations do not cover the world's forest areas evenly. For example, data points from the boreal forest areas are concentrated within Canada and Northern Europe, while points in Russia are sparse (Fig. S.2). We tried to overcome this issue partially by including subnational proxies on primary and plantation forests. Furthermore, the PREDICTS database – the source for most of our data points, is not intended to report forest management. The occurrence of timber logging does not necessarily determine production forests, which was, however, something we postulated in this study. Additionally, the described area might be just an exception in the matrix of a different forest or land use class. This lack in amount and quality of validation and training data entails that many places would likely be classified differently by local experts compared to our results. This is especially the case for areas with poor ground data, such as China, the remote Amazon, or the tropical forests of Africa. Our maps visualize the need for a consistent and comprehensive database on ground data for forest management.

Summarizing, the presented maps have still uncertainties and reflect some well-known problems with the underlying FRA statistics. It should, therefore, not be regarded as a ‘true’ map of global patterns of forest classes and uses. Future applications, especially non-global studies, need to thoroughly evaluate the underlying national data extents, e.g. with the FRA country reports, beforehand. It is crucial to understand that differences in extents and patterns are often due to inconsistent interpretations of forest classes and uses, rather than actual differences of the forest properties. Also, the mapped forest categories are not forest management classes. Although being the result of (past) management, they do not equal actual management. It is not possible to derive from these maps, which silvicultural measures a forest manager might deploy or if conventional or alternative harvest practices are

conducted. It can be assumed that in forests used for multiple purposes harvest strategies are more sustainable (García-Fernández et al., 2008), to minimize the impact on other uses, such as biodiversity protection or recreation. But in some countries, multiple-use forests comprise clear-cut next to wilderness areas (Zhang, 2005) and sustainable harvest practices can also be found in forests primarily used for timber (Duncker et al., 2012a).

Nevertheless, these maps are a first step to map global forest management and are improving our understanding of these patterns substantially. The product is bringing together the best knowledge and currently available data. It is complementary to existing products, by providing spatial allocation of forest classes and uses that have not been mapped before. The maps perform better than random and locations of plantation forest deviate mostly not more than 10 km to other data and observations. They can therefore be used to improve global studies on land management for climate change mitigation and biodiversity protection. Potential applications include the support of assessing priority areas for protected area networks by providing an indication of the naturalness of a forest area. So far, only close and open forests are distinguished, whereby both have very high values of naturalness (Montesino Pouzols et al., 2014). They can also improve research on global land-based climate change mitigation strategies. Land modelling approaches estimating future scenarios on land-based mitigation do currently take into account afforestation and avoided deforestation, but forest management types are lacking (Kim et al., 2006; Lotze-Campen et al., 2008; Stehfest et al., 2014). Furthermore, due to the consistent and simple approach we used, it is easily possible to advance upon with other methods and more detailed information once available, such as improved national statistics, e.g. the upcoming FRA 2020, ground-based information and/or citizen science contribution. Both maps are available and freely accessible at www.environmentalgeography.nl.

Acknowledgements

The authors would like to thank the European Commission for funding through the European Research Council under the European Union's Seventh Framework Programme project ID 311819 (GLOLAND), project ID 603542 (LUC4C), and project ID 308393 (OPERAS).

Declaration of interest

The authors declare that there is no conflict of interest.

Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.foreco.2018.10.001>.

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