Forest Ecology and Management 357 (2015) 228–238

Contents lists available at ScienceDirect

Forest Ecology and Management

journal homepage: www.elsevier.com/locate/foreco

Mapping wood production in European forests

Pieter J. Verkerk [a,*], Christian Levers [b], Tobias Kuemmerle [b,c], Marcus Lindner [a], Ruben Valbuena [a], Peter H. Verburg [d], Sergey Zudin [a]

[a] European Forest Institute, Sustainability and Climate Change Programme, Yliopistokatu 6, 80100 Joensuu, Finland
[b] Geography Department, Humboldt-Universität zu Berlin, Unter den Linden 6, 10099 Berlin, Germany
[c] Integrative Research Institute for Transformations in Human Environment Systems (IRI THESys), Humboldt-Universität zu Berlin, Unter den Linden 6, 10099 Berlin, Germany
[d] Institute for Environmental Studies, VU University Amsterdam, De Boelelaan 1087, 1081 Amsterdam, The Netherlands

ARTICLE INFO

Article history:
Received 28 April 2015
Received in revised form 31 July 2015
Accepted 6 August 2015
Available online 31 August 2015

Keywords:
Forest productivity
Europe
Location factors
Spatial patterns
Disaggregation
Downscaling

ABSTRACT

Wood production is an important forest use, impacting a range of other ecosystem services. However, information on the spatial patterns in wood production is limited and often available only for larger administrative units. In this study, we developed high-resolution wood production maps for European forests. We collected wood production statistics for 29 European countries from 2000 to 2010, as well as comprehensive sets of biophysical and socioeconomic location factors. We used regression analyses to produce maps indicating the harvest likelihood on a 1×1 km^2 grid. These likelihood maps were validated using national forest inventory plot data. We then disaggregated wood production statistics from larger administrative units to the grid level using the harvest likelihood as weights. We verified the resulting wood production maps by correlating predicted and observed wood production at the level of smaller administrative units not used for generating the wood production maps. We conclude that (i) productivity, tree species composition and terrain ruggedness are the most important location factors that determine the spatial patterns of wood production at the pan-European scale and that (ii) incorporating these location factors substantially improves the results of disaggregating wood production statistics compared to a disaggregation based on forest cover only. Our wood production maps give insight into forest ecosystem service provisioning and can be used to improve the assessment of potentials and costs of woody biomass supply.

1. Introduction

Forests provide a broad range of ecosystem services that are important to human society (Millennium Ecosystem Assessment, 2005). Wood production represents a key provisioning service and global wood production amounted to 3.4 billion m^3 in the year 2005 (FAO, 2010). Because wood production affects the provisioning of other services and biodiversity (Schwenk et al., 2012; Verkerk et al., 2014a; Zanchi et al., 2014), spatially explicit information on wood production is important for the design and implementation of policies targeted at sustainable forest use (cf. Cowling et al., 2008; Maes et al., 2012).

Statistical information on wood production can be combined with land-cover maps (i.e., forest cover maps) to develop wood production maps (Maes et al., 2012). Yet, the use of forest cover as the only proxy to map wood production is a coarse and simplistic approach that may result in substantial errors (Eigenbrod et al., 2010), because production patterns may not be equally distributed across forested landscapes (Wendland et al., 2011; Masek et al., 2011). This suggests that determinants other than forest cover should be considered when mapping wood production patterns.

A few studies have recently attempted to map wood production, or forest management in general. For example, Hurtt et al. (2006) mapped wood production at a global level, assuming that forest cover and proximity to transportation infrastructure determined the spatial patterns of production. Within Europe, Hengeveld et al. (2012) mapped different forest management alternatives and identified areas with intensive forest management focusing on wood production, as well as areas with management objectives other than wood production. Furthermore, Levers et al. (2014) mapped harvesting intensity across European forests (i.e., wood production in relation to the net annual increment) and assessed the drivers of harvesting intensity at the level of administrative units. They found that harvesting intensity is driven by a combination of forest-resource related factors (i.e., the share of plantation species, growing stock, forest cover), site conditions (i.e., topography, accessibility), and country-specific characteristics.

* Corresponding author.
E-mail address: hans.verkerk@efi.int (P.J. Verkerk).

http://dx.doi.org/10.1016/j.foreco.2015.08.007
0378-1127/

However, their analysis focussed primarily on understanding drivers of harvesting intensity and was restricted to exploring spatial patterns for larger administrative units (national to provincial level or forestry districts) thereby not addressing wood production at the grid level.

Existing studies suggest that knowledge of the factors driving patterns in wood production can improve the disaggregation of wood production statistics substantially. In such an approach first a statistical relationship between a target variable (e.g., wood production) and its location factors (e.g., soil quality, topography, accessibility) is established at the level of the aggregated target data (e.g., for administrative units). Second, this relationship is then used to predict the suitability of every location for the target variable at the target grid level for which information on the location factors are available. Such a downscaling approach in which statistical relationships are transferred across scales is called dasymetric mapping (Eicher and Brewer, 2001) and has been used extensively to disaggregate national- or regional-level land-use extent (Dendoncker et al., 2007), farming systems (van de Steeg et al., 2010), livestock (FAO, 2007; Neumann et al., 2009), or nitrogen input (Temme and Verburg, 2011). In a forestry context, dasymetric mapping was used to derive gridded maps of tree species presence for Europe (Brus et al., 2012) and at the global scale to map growing stock, forest biomass (Kindermann et al., 2008) and wood production (Hurtt et al., 2006). The latter maps have been generated at a resolution of $1° \times 1°$ grid cells, using coarse, national-scale data on wood production, mainly targeted as an input for global climate and vegetation models. These applications strongly highlight the potential for dasymetric mapping to provide insights into wood production patterns, but a fine-scale application of this kind is missing for Europe, and as a result the spatial patterns of wood production remain weakly understood.

Here, we present an approach to fill this knowledge gap by developing high-resolution wood production maps for European forests (in this study limited to 27 European Union member states, plus Norway and Switzerland) for the period 2000–2010 at a resolution of 1×1 km^2 grid cells. Our objectives were (1) to analyse the location factors determining wood production patterns in Europe, (2) to assess whether information about the relationship between wood production and location factors improves the disaggregation of wood production statistics, and (3) to derive time series of wood production maps for Europe.

2. Material and methods

2.1. Data

2.1.1. Wood production data

We collected data on wood production from national forestry reports, statistical yearbooks and databases, and by contacting national experts known to the authors (Table S1 in the Supplementary Material) for the years 2000 to 2010 for 460 administrative units within the 29 countries in our study. The number of administrative units per country varied from 1 (national level) to 107 (provincial or forestry district level). The statistics that were collected followed national definitions and differed in e.g. whether wood production volumes were reported as over or under bark, or included harvest losses. To account for these differences, we harmonised the wood production data by calculating the share of harvested wood volume for each administrative unit relatively to the national total wood production. These shares were calculated as averages for all years for which regional data was available in our dataset. Shares were then multiplied with national-level harvest data. For the latter, we used annual roundwood production (m^3 under bark) statistics from FAOSTAT (2012), because these data are reported following harmonised definitions and data were available for each year in our study period. To use the data for statistical analyses, we divided harvest volume by forest area in each region (Table S2 in the Supplementary Material). To mitigate problems due to differences in national definitions, we calculated the area share of each unit in the total forest in a particular country and multiplied it with the forest area in 2000 according to Forest Europe et al. (2011). The outcome was a set of maps of harmonised wood production statistics [*WOOD*; m^3 ha^{-1} yr^{-1}] at the level of administrative units.

2.1.2. Location factors

We reviewed literature to identify potential location factors that could affect the likelihood of harvesting at a given location. The literature review focussed on understanding the harvesting behaviour of forest owners (Beach et al., 2005; Bolkesjø et al., 2007; Butler, 2006; Favada et al., 2009; Størdal et al., 2008; Vokoun et al., 2006; Adams et al., 1991; Arano and Munn, 2006), as well as on wood supply in more general terms (Sterba et al., 2000; Verkerk et al., 2011). Based on our review and data availability for the entire study area, 16 potential location factors influencing the likelihood of harvest were identified, as well as a priori assumptions with regards to the direction of influence of each location factor on harvesting likelihood (Table 1). This set of potential location factors is similar to the set used by Levers et al. (2014). A key difference is that we used net annual increment as an additional predictor, as it may strongly influence the location of wood production, whereas Levers et al. (2014) used net annual increment to normalise harvest in order to obtain a more direct indicator of harvesting intensity at the level of administrative units.

Most data on location factors were available as raster maps with a resolution of 1×1 km^2 grid cells. Where data were available at a finer resolution, we aggregated them using bilinear interpolation based on the weighted distance of the four nearest input cell centres. Data layers that were available for administrative units were rasterized to the 1×1 km^2 grid assuming homogeneity across administrative units. Maps of the location factors are shown in Fig. S1 in the Supplementary Material. Details on the data preprocessing of the predictor variables are provided in the Supplementary Material of Levers et al. (2014).

To match the spatial resolution of our location factors to that of the wood production statistics, we calculated average values of our location factors for each of the administrative units for which we had collected wood production statistics. In case location factors were not limited to forests (e.g., *POORSOIL* in Table 1), we weighted location factor values according to forest cover for each administrative unit. To do so, we multiplied relevant location factor maps with a fractional forest cover map. We used the forest map by Pekkarinen et al. (2009), which was calibrated following an approach by Päivinen et al. (2001) to match regional-and national-level forest area statistics (Section 2.1.1; Table S2 in the Supplementary Material). As a result, the values of location factors at locations with higher forest cover had a larger share in the average predictor value at the administrative unit level, compared to pixels with little forest cover.

We also investigated possible collinearity between location factors, but did not find correlation coefficients exceeded 0.7 (Fig. S2 in the Supplementary Material) and therefore considered all location factors for subsequent regression analyses.

2.2. Regression analyses

To analyse how our set of location factors influences the spatial patterns of wood production, we employed two regression techniques: (1) a model selection using traditional, linear regression modelling combined with Bayesian Model Averaging (BMA) and