Estimating future wood outtakes in the Norwegian forestry sector under the shared socioeconomic pathways

Abstract

The forest sector plays a key role in achieving low temperature stabilization targets, as woody biomass represents a cost-efficient alternative to fossil fuels for energy and material production. Estimates of future woody biomass demands vary in the Shared Socioeconomic Pathways (SSPs), depending on societal development trends, climate model projections, socioeconomic conditions, and climate and energy policies. The SSPs are qualitatively and quantitatively defined at global and macro-regional level, and their implementation for individual sectors at a national basis is challenging. In this paper, we provide estimates for forest wood outtakes in Norway until 2100 using key drivers from the SSPs such as population and Gross Domestic Product (GDP) and specific aspects of land use sector. First, we analyze historical wood harvest trends from 1960 to 2016 for the main tree species and wood classes and construct a regression model based on population, GDP and time. The model is then adapted and modified according to salient characteristics of the different SSP scenarios for a developed country such as Norway to estimate future outtake volumes for each combination of tree species and wood class. These estimates are produced after interpretation and implementation in the model framework of SSP specific aspects like GDP and population trends, land-use change regulation, participation of the land-use sector to climate change mitigation, and starting year for international cooperation for climate change mitigation. The produced estimates span a range of possible harvest rates and resource use potentials. Results show that SSP5 is the most resource intensive scenario, with harvest rates achieving 27.5 million m^3 in 2100. Driven by high population and GDP, SSP5 exceeds the forest maximum harvest potential in Norway. It is followed by SSP1, which achieves a maximum mean extraction rates of 17.7 (in 2090), about 64% of the maximum extraction rate in SSP5. Forest wood outtake volumes are the lowest in SSP3, reaching a maximum of about 11.9 million m^3 in 2040 and then declining. SSP2 and SSP4 generally lie in between SSP1 and SSP3. Variability in the estimates is larger when land use regulation is weak and market fluctuations are high, such as in SSP2, SSP3 and SSP5. The proposed model framework is an approach to interpret and translate the global qualitative SSP narratives into quantitative projections at a finer scale, and can favor the use of a consistent background setting such as the SSPs in interdisciplinary research activities across different spatial scales of analysis.

Keywords: Forestry; bioenergy; SSP; climate change mitigation; regression models.

1 Introduction

Forestry products are key for the climate-energy-material nexus (Creutzig et al., 2015, Sikkema et al., 2017, Fulton et al., 2015), and management of bioresources will play a major role to achieve low temperature stabilization targets (Popp et al., 2014b, Lauri et al., 2017). Forest products can contribute to supply of renewable biomass for energy and construction materials, which are predicted to increase in a more sustainable future (Lauri et al., 2017, Van Vuuren et al., 2011), and forestry projects are valuable instruments to achieve emission reduction targets (van der Gaast et al., 2016). High resolution information and future estimates of wood outtakes and material products is key for studying the biophysical basis of socioeconomic metabolism and resource potentials (Pauliuk et al., 2015), for characterizing the role of environmental stocks in human development and emission growth (Lin et al., 2017), and, more particularly, for assessing the climate change impacts of transformation in the dwelling and wood industry subsectors (Pauliuk et al., 2013).

The Shared Socioeconomic Pathways (SSPs) describe alternative societal development trends over the next decades through combinations of different scenarios for climate model projections, socioeconomic conditions, and climate and energy policies (O’Neill et al., 2014, Ebi et al., 2014, Van Vuuren et al., 2014). These integrated future scenarios are designed to serve the scientific community in facilitating the adoption of a common and harmonized framework for interdisciplinary research in the field of climate change mitigation and adaptations and to study future changes in technological, societal, and environmental systems. Extensive quantitative and qualitative information about the SSPs are today available, with descriptions of the characteristics of the different SSP components (Riahi et al., 2017, O'Neill et al., 2017, Popp et al., 2017, Fujimori et al., 2017, Kriegler et al., 2017, Calvin et al., 2017, Fricko et al., 2017). The SSPs are based on five narratives describing alternative socio-economic developments, including sustainable development, regional rivalry, inequality, fossil-fueled development, and middle-of-the-road development (Riahi et al., 2017). The five SSPs have different land-use change regulations and land-based mitigation policies (O'Neill et al., 2014). In SSP1 (“taking the green road”), the world shifts towards a sustainable path. There is a strong land-use change regulation with international efforts to minimize environmental impacts and tradeoffs. This scenario envisions a full participation of the land-use sector, and there is no delay (i.e., starting from 2020) in the international cooperation for climate change mitigation. In SSP2 (“middle of the road”), the world follows a path that does not shift markedly from historical patterns, and the land-use change regulation is incomplete (medium regulation). There is a partial participation of the land-use sector and the international cooperation for climate change mitigation is delayed to 2030. In SSP3 (“regional rivalry—a rocky road”), countries are more concerned about domestic issues and competitiveness, with lower attention to climate and environmental aspects. There is limited or almost no regulation on land-use change, and the participation of land-use sector is also limited. International cooperation for climate change mitigation is delayed to 2040 for high-income countries and to 2050 for the rest of the world. In SSP4

(“Inequality—A road divided”), there will be increasing inequalities in the development of the different countries. There is a partial participation of the land use sector, and only developed countries introduce strong regulation to land-use change with no delay in the international cooperation for climate change mitigation (starting in 2020). In SSP5 (“fossil-fueled development—taking the highway”), the world will strengthen the role of competitive markets, and the regulation of land-use change is incomplete. Compared to SSP2, there is full participation of the land-use sector with a delay of international cooperation for climate change mitigation to 2040. We refer to (O'Neill et al., 2014) for more detailed discussion on the narratives of SSPs, and to (Popp et al., 2017) for the specific focus on the land use component.

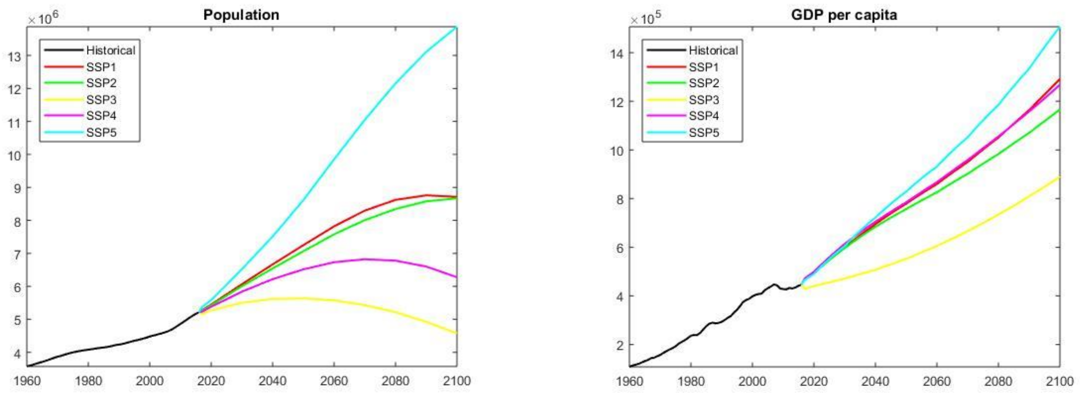
The SSPs are defined at a global and macro level, and regional/sectorial extensions are seen as critical next steps for future applications (Riahi et al., 2017, Absar and Preston, 2015). The core principles of their different narratives can be used as drivers to estimate future developments of individual and smaller-scale sectors. This has the potential advantage to consolidate interdisciplinary research under a common framework and different spatial scales of analysis. Future forest wood outtakes can be estimated within an integrated impact assessment framework using sophisticated non-linear recursive dynamic optimization models or partial equilibrium models that are linked to spatially explicit biophysical constraints (Popp et al., 2014a, Humpenöder et al., 2015, Havlík et al., 2014). These models, such as the economic model GLOBIOM (Global Biosphere Management Model) (Havlik et al., 2011, IIASA, 2017, Havlík et al., 2012) and the recursive dynamic optimization model MAgPIE (Model of Agricultural Production and its Impact on the Environment) (Lotze-Campen et al., 2008, PIK, 2017), are rather complex and global in scope, although they can be used for regional and/or grid-level applications. In this study, we use a simpler approach and develop a bottom-up model framework based on historical data (from 1960 to 2016) of forest wood outtakes in Norway using country-specific information on tree species (birch, pine and spruce) and wood classes (sawn wood, pulpwood, bioenergy, and unsorted logs). Multiple linear models with GDP per capita and time as explanatory variables are adopted to describe the historical trends in harvest rates (normalized to population) for each combination of tree species and wood class. White Gaussian noise processes are introduced to capture the randomness of market fluctuations. The model is based on a double-logarithmic formula which allows to explicitly include the effects of GDP and populations. Future projections of wood outtakes from Norwegian forests over the twenty-first century are developed to be consistent with the narratives of the different SSPs, after introducing in the model the key drivers of the SSPs and an interpretation of specific aspects of land use sector. These include the specific GDP and population trends, and the values of estimated parameters for time regression and noise processes are modified according to different policies in terms of land-use change regulation, participation of the land-use sector to climate change mitigation, and starting year of international cooperation for climate change mitigation. This can bridge (and downscale) the major SSP global framework with the dynamics of an individual sector at a country level.

2 Methodology

2.1 Data gathering

The total forested area of Norway amounts to about 12 million hectares (about 38% of the country's total surface area), of which more than 7 million hectares are productive forest. The most important tree species are coniferous, mostly Norway spruce (Picea abies) (47%) and Scots pine (Pinus sylvestris) (33%), and deciduous species (mostly Betula pubescens and Betula pendula) (18%). Historical data for the harvested wood product sector in Norway are gathered from the Norwegian national statistics in terms of commercial roundwood removals from 1960 to 2016 (SSB, 2017a). The dataset includes information about wood harvests for three species of trees (spruce, pine, and birch) and four types of wood classes (sawlog, pulpwood, unsorted sawlog/pulpwood and fuelwood). In the period 1960-1979, official data are only available for individual tree species and not for the different wood classes. It is assumed that distribution of wood classes among species reflects the average shares for each tree species in the time interval 1980-1989.

The historical population from 1960 to 2016 is obtained from the Norwegian national statistics (SSB, 2017d). The historical GDP by expenditure in fixed price per capita (relative to 2005) is obtained from the Norwegian Central Bank (Norges-Bank, 2017) for the period 1960-1969, and from the Norwegian National statistics for the period 1970-2016 (SSB, 2017b). The future national estimates of GDP and population from 2017 to 2100 are obtained from the SSP Public Database hosted at the International Institute for Applied Systems Analysis (IIASA) (SSP-Database, 2017). Data are available at a 10 year time step interval, and are connected through linear interpolation. The historical and future trends of population and GDP are shown in Figure 1. The strongest growth in population occurs under SSP5, where it increases from 5.21 million in 2016 to 13.9 million in 2100. On the other hand, population is expected to decline to 4.57 million in 2100 under SSP3. Similarly, GDP per capita shows the steepest increase under SSP5, and the smallest variations under SSP3.



(a) (b)

Figure 1 Population (a) and GDP per capita (b) in Norway from 1960 to 2100. Data from 1960 to 2016 are from historical records, and data from 2017-2100 are from the SSP public database. Units: Population: Person; GDP: NOK/person

2.2 Model framework and integration with SSP scenarios

Three steps are used for generating future wood harvest scenarios in Norway under the different SSP scenarios. We first construct a multiple linear regression model of historical wood outtakes and estimate the parameters. We then integrate the key drivers of the different SSP scenarios and the aspects of the land use sector into the model framework to estimate future scenarios of wood harvest rates. Finally, the predicted wood harvest rates are aggregated for each SSP, and an analysis of the maximum harvest potential as a constraint is introduced to calibrate model outcomes.

The first step is to use the historical wood harvest dataset to make a regression analysis. The model has the following form, which is adapted from the double-logarithmic formula (Houthakker, 1965),

$$\log\left(\frac{Q_{ij}}{P_t}\right) = a_{ij} \times \log(G_t) + b_{ij} \times t + c_{ij} + \varepsilon_{ij}, \qquad i = 1,2,3,\ j = 1,2,3,4 \tag{1}$$

where the indexes i and j represent the species of trees and the wood classes, respectively. P_t and G_t stand for population and GDP per capita at year t, and Q_{ij} stands for the amount of harvested wood for different species and wood classes. The parameters a_{ij} and b_{ij} are the coefficients for the explanatory variables, and c_{ij} is the intercept parameter of the regression lines. ε_{ij} is the white noise process, assumed to have a Gaussian distribution with mean zero and variance σ_{ij}^2. This regression model has a simple interpretation. The regression line captures the trend of the wood harvest, with parameters a_{ij} and b_{ij} indicating the influence of GDP per capita and time for wood species i and wood class j, and the white noise term captures the fluctuation of the market.

The overview of the data distribution of the historical harvested wood per capita is shown in Figure 2 using boxplots. The figure shows the distribution of the data log(q_{ij}), where $q_{ij}=Q_{ij}/P_t$, for each individual combination of tree species and wood class. In order to obtain robust estimation, outliers in the dataset (indicated as red + in Figure 2) are detected and filtered out. The parameters $\theta_{ij} = \left\{a_{ij}, b_{ij}, c_{ij}, \sigma_{ij}\right\}, i = 1,2,3,\ j = 1,2,3,4$ in Equation (1) are estimated from the dataset for each wood species and corresponding wood classes.

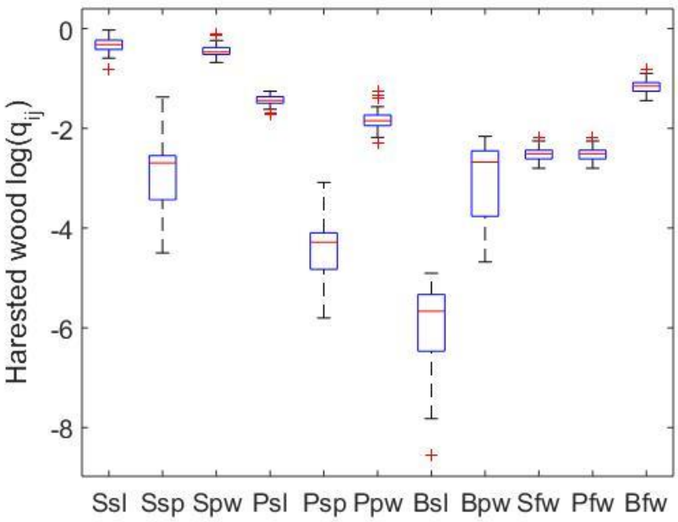


Figure 2 Boxplot of the harvested wood per capita in Norway for the different tree species and wood classes (unit: m^3 per capita in log scale). The central red line in each box indicates the median, and the bottom and top edges of the box are the 25th and 75th percentiles, respectively. The whisker indicates 1.5 times of the 75th percentile-25th percentile to the bottom or top edge of the box. The outliers are the points that fall outside of the whisker and are indicated with the red '+' symbol. On the horizontal axis, there are the different wood species and classes. The first upper-case letters stand for the different species of trees, with S for spruce, P for pine and B for birch. The second and third lower-case letters stand for wood classes, with sl for sawlog, sp for unsorted sawlog and pulpwood, pw for pulpwood and fw for fuelwood. The boxplot of birch used as unsorted sawlog and pulpwood (Bsp) is not shown since the values are too small.

In the second step, the key drivers of SSP scenarios such as population and GDP are used and the aspects of land use sector are integrated into the model framework by translating the qualitative narratives into quantitative formulas. We adjust the coefficients of the explanatory variable t and the variance parameter of the white Gaussian noise process according to the different degrees of participation of the land-use sector to climate change mitigation and different land-use change regulations. We also change future GDP and population in line with the different trends in the SSPs. In addition, a weight parameter ρ is introduced to better control and differentiate the rate of changes for the individual combinations of tree species and wood classes (see Table 1). Some tree species and wood classes will have different preferential applications, with different effects on future estimates. For instance, wood from birch trees is more suitable for fuelwood (ρ = 0.5) than other species (ρ = 0.25), whereas wood from spruce and pine is preferentially used as sawlog. We set the values of the parameters ρ_{ij} to -0.5 for pulpwood because paper demand will likely decline in the future, whereas uses of wood for energy applications and construction materials are likely to increase. The other values are set with similar considerations.

Table 1 Values of weight parameter ρ_{ij}. See caption of Figure 2 for the legend.

Ssl	**Spw**	**Ssp**	**Sfw**	**Psl**	**Ppw**
0.25	-0.5	-0.25	0.25	0.25	-0.5
Psp	**Pfw**	**Bsl**	**Bpw**	**Bsp**	**Bfw**
-0.25	0.25	-0.5	-0.5	-0.5	0.5

In addition to the SSP key drivers GDP and population, the aspects of land use sector from different SSPs considered in our work are summarized in Table 2 with the parameters for their implementation in the model. The variance parameter σ_{ij}^2 is initially estimated from the historical dataset and its future changes follows the land use change regulations in the SSPs as defined in Table 1 in (Popp et al., 2017). As it can be interpreted in terms of market fluctuations and lack of a clear policy, it is reduced to one-fourth (relative to the historical estimate) in case of strong regulations of the land use sector (SSP1 and SSP4), where market fluctuations can be expected to be less pronounced. It is decreased to one-half in case of incomplete regulations (SSP2 and SSP5) and remains of the same breadth for SSP3, where there is limited or no regulation. The parameter δ (in percentage) describes the mean change in the supply of the specific wood product connected to the participation of land use sector to climate change mitigation as specified in Table 1 in (Popp et al., 2017), and it scales the weighting factor ρ. When the participation is full (SSP1 and SSP5), there is a major supply of bioresources for renewable energy and material products, and the parameter δ is set to 1 (meaning that the weighting factor is fully deployed). When the participation is partial (SSP2 and SSP4), δ is set at 0.5, and it becomes 0 when there is limited or no participation of the land use sector to climate change mitigation (SSP3).

Table 2 Overview of the SSP scenarios with the aspects in land use sector for tweaking model parameters.

	SSP1 (Sustainability)	SSP2 (Middle of the Road)	SSP3 (Regional Rivalry)	SSP4 (Inequality)	SSP5 (Fossil-fueled Development)
Land-use change regulation	Strong	Incomplete	Limited or no	Strong	Incomplete
Participation in land-use sector	Full	Partial	Limited or no	Partial	Full
Cooperation for climate change and mitigation	No delay	Delayed	Limited or no	No Delay	Delayed
Starting year of mitigation t_k	2020	2030	2040	2020	2040
Parameter δ	1	0.5	0	0.5	1
Variance parameter σ^{p2}	Decreased to one forth	Decreased to half	No change	Decreased to one forth	Decreased to half

The model for predicting future wood harvest rates in Norway according to the SSPs can thus be written as follows:

$$\log\left(\frac{Q_{ijk}^{p}}{P_{kt}}\right)=\begin{cases} a_{ij}\times\log\left(G_{kt}\right)+b_{ij}\times t+c_{ij}+\varepsilon_{ij}, 2017\leq t<t_k & i=1,2,3,\ j=1,2,3,4,\\ \hat{y}_{ijk}^{l}+a_{ij}\times\log\left(G_{kt}\right)+(b_{ij}+\rho_{ij}\times\delta_k)\times\left(t-t_k\right)+\varepsilon_{ijk}^{p}, t_k\leq t\leq 2100, & k=1,2,3,4,5\end{cases} \quad (2)$$

where the indexes i, j and k indicate different wood species, wood classes and SSP scenarios, respectively. The parameters a_{ij} and b_{ij} are estimated from the historical wood harvest dataset using equation (1). The estimated future population P_{kt} and GDP per capita (G_{kt}) are obtained from the SSP public database for each SSP k and linearly interpolated. $q_{ijk}^{p}=Q_{ijk}^{p}/P_{kt}$ is the predicted volume of harvested wood per capita for species i and wood class j in year t. The parameter t_k denotes the starting year of participation of the land use sector to climate change mitigation. This means that the first expression of equation (2) refers to the extrapolation of the historical trend until t_k, and the second expression includes the modified parameters according to the specific SSP scenario. The intercept term $\hat{y}_{ijk}^{l}$ is the estimated wood harvest at the last year $(t_k - 1)$ before participation in the international cooperation for climate change mitigation for each species of trees i, wood class j, and SSP scenario k, and δ_k links the change of the trend with time t under SSP scenario k after participation of land use sector. The white noise process ε_{ijk}^{p} has the value of the variance σ_{ijk}^{p2} estimated from the historical trend (1960-2016) until t_k, and it is then modified for the different land-use change regulations of the SSPs as shown in Table 2. A transition period of 10 years is also assumed to reflect the market response to the new policy after cooperation for climate change mitigation has started. In the period $t_k < t < t_k +10$, the variance σ_{ij}^{2} linearly decreases to the new value σ_{ijk}^{p2} for each scenario k.

The predicted total wood harvest Q_k^p for each SSP scenario is then obtained by aggregating the prediction of all tree species and wood classes,

$$Q_k^p=\sum_{i=1}^{3}\sum_{j=1}^{4}Q_{ijk}^{p}, \qquad i=1,2,3,\ j=1,2,3,4, k=1,2,3,4,5 \quad (3)$$

with $Q_{ijk}^{p}=q_{ijk}^{p}*P_{kt}$.

2.3 Wood harvest with resource constraint

The total wood harvest Q_k^p under each SSP scenario k can be compared with the maximum harvest potential in Norwegian forests, which can be introduced as a constraint to calibrate model outputs. The mean annual increment of Norwegian woody biomass is approximately 25.8 million m^3 per year (SSB, 2017c), meaning that Norway is currently extracting 44% of the wood resources available.

This mean annual increment represents the upper limit of wood harvest and the potential for the growth of the harvest wood product sector in Norway. We use this as a constraint in the model applied to either the mean trend or the 95% of the confidence interval of the predictions for each SSP. Although it may change in the future under a changing climate and different extraction rates, we simply assume the mean annual increment of Norwegian forests as time-invariant. Its future changes are difficult to predict owing to the different factors at play, and its magnitude did not significantly change in the past years (it had little variations in the past couple of decades, oscillating between 24.5 million m^3 in 2000 to 25.8 million m^3 in 2017).

The condition for which the predicted mean harvested wood should not exceed the resource constraint can be written as

$$Q_k^p \leq \omega \times 25.8 \text{ million m}^3, \qquad k = 1, 2, 3, 4, 5 \tag{4}$$

Q_k^p denotes the predicted mean wood harvest with SSP scenarios *k*. On the other hand, when the upper bound of the predicted 95% confidence interval is taken into account, the wood resource constraint can be written as

$$Q_k^{pCI} \leq \omega \times 25.8 \text{ million m}^3, \qquad k = 1, 2, 3, 4, 5 \tag{5}$$

Q_k^{pCI} denotes the predicted upper bound of the 95% confidence interval of the aggregated wood harvest under SSP scenario *k*. In both equations (4) and (5), the parameter ϖ is defined in the interval $0 \leq \omega \leq 1$ and controls the fraction of the forest annual increment allowed to be harvested. We assume $\varpi = 0.7$ on the basis of the more extended harvested wood product sector in Sweden, where up to 70% of the mean annual increment is harvested. This makes the upper limit of wood harvest rates in Norway equal to 18.06 million m^3. This constraint is then applied to the model by introducing a factor α to modify the time coefficient,

$$b_{ijk}^{'} = b_{ij} + \delta_k * \rho_{ij} + \alpha, \quad i = 1, 2, 3, \; j = 1, 2, 3, 4, k = 1, 2, 4, 5 \tag{6}$$

The value of α is estimated for each individual SSP by taking into account the relationship between the constraint and either the mean or the upper bound of the 95% of the confidence interval of the predictions. The factor α is independent of tree species, wood classes and different scenarios of population and GDP. Therefore, this setting can be uniformly applied to all tree species and wood classes with different SSPs, for which one independent value of α is computed. SSP3 is excluded because there is no or limited participation of the land use sector to climate change mitigation and land-use policies ($\delta = 0$). The factor α is determined starting from zero with a step size of $1 \cdot 10^{-5}$. The iteration is stopped when the harvest rate achieves the resource constraint in a certain year, which corresponds to the year of maximum harvest rate in each SSP. When $\alpha > 0$ the harvested wood rates will increase, and it will decrease with $\alpha < 0$. When $\alpha = 0$, we return to the settings given in

Table 1 and Table 2.

3 Results and discussion

Firstly, the results from the regression analysis of the historical wood harvest dataset are presented. Secondly, we illustrate the results of the model for future wood harvest until 2100 according to different SSP scenarios. Model outputs are finally benchmarked and calibrated with the wood resource constraints of Norwegian forests.

3.1 Regression of the historical dataset

Using the historical harvested wood with population and GDP datasets, we estimate all the parameters of the linear model in equation (1) for different tree species and wood classes in Norway. The historical trends and the model outputs are shown in Figure 3. Spruce and pine are mainly used as sawlog and pulpwood, and Birch is mainly used as fuelwood (Figure 3a). Spruce as sawlog and pulpwood generally cover the largest fractions of the volume of harvested wood in Norway (around 58% on average), followed by pine as sawlog and pulpwood and birch as fuelwood with about 17 and 13%, respectively. Birch is rarely used as sawlog and pulpwood (less than 3%), whereas it is the dominant species for bioenergy use. On the other hand, pine and spruce are mostly used for material applications, with little fractions used for bioenergy. In general, data for total wood harvest rates in Norway show a historical increasing trend with large market fluctuations (Figure 3b). The peak in extraction rates was achieved from 1987 to 1989 and it is mainly driven by high demands for spruce and pine as pulpwood and sawlog. From 2003, the volume of harvest wood steadily increases and this might be correlated to increases in oil prices. The estimated coefficients α_{ij} and b_{ij} for explanatory variables G_t and t, the intercept parameters c_{ij}, and the standard deviations σ_{ij} (square root of the variance σ_{ij}^2) of the white noise process are given in Table 3 for each combination of tree species and wood classes. In general, GDP and time have different influence to the wood harvest rates, except for spruce as pulpwood where they have the same sign. Time positively contributes to pine as sawlog but negatively to spruce as sawlog. This means that spruce as sawlog has the tendency to decline whereas pine as sawlog has the tendency to increase with fixed GDP and population. For fuelwood, GDP positively contributes for all different tree species since a_{ij} is positive, but time has a negative effect (b_{ij} is negative).

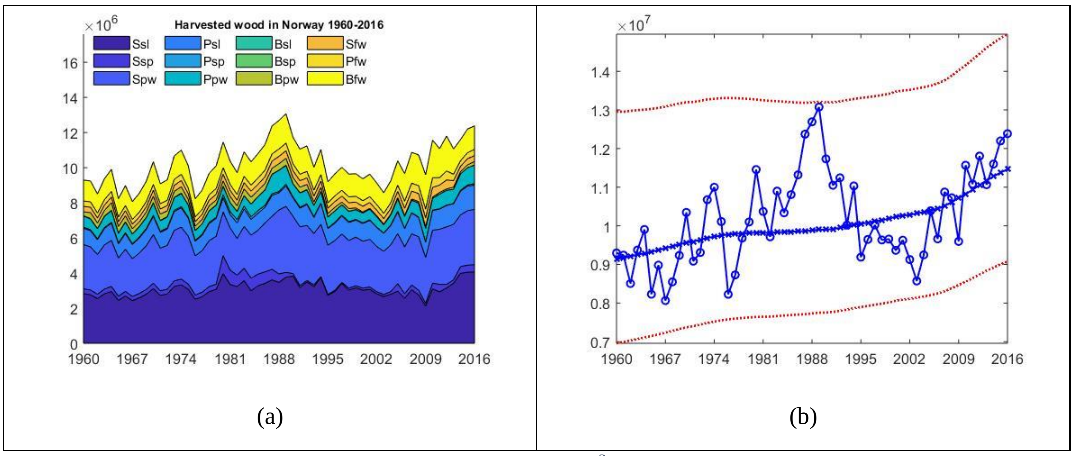


Figure 3 Historical wood harvest rates from Norwegian forest in m^3. (a) Breakdown of total outtakes per tree species and wood class (see caption in Figure 1 for the legend). (b) Trends for the total wood harvest rates from our linear regression model. The blue solid line is the regression line with x indicating the estimated mean harvested wood using our model. The red dotted lines indicate the 95% confidence interval of the estimates. The observed total wood harvest is given in blue circles and connected with solid lines.

Table 3 Estimated parameters of the regression model for historical wood harvest rates in Norway. The parameters *a* and *b* are the coefficients of GDP and time, respectively, c is the intercept of the regression line for different wood species and classes, and *σ* is the standard deviation of the Gaussian noise process. See caption of Table 1 for the legend.

	Ssl	Ssp	Spw	Psl	Psp	Ppw
a	$1.75\cdot10^{-1}$	$-7.59\cdot10^{-1}$	$-1.75\cdot10^{-2}$	$-2.45\cdot10^{-1}$	1.40	$-6.14\cdot10^{-1}$
b	$-7.22\cdot10^{-3}$	$5.24\cdot10^{-3}$	$-1.06\cdot10^{-3}$	$6.64\cdot10^{-3}$	$-5.91\cdot10^{-2}$	$1.55\cdot10^{-2}$
c	-2.30	6.47	$-2.09\cdot10^{-1}$	1.45	$-2.02\cdot10^{1}$	5.35
σ	$1.17\cdot10^{-1}$	$6.62\cdot10^{-1}$	$8.95\cdot10^{-2}$	$8.38\cdot10^{-2}$	$4.82\cdot10^{-1}$	$1.32\cdot10^{-1}$
	Bsl	**Bsp**	**Bpw**	**Sfw**	**Pfw**	**Bfw**
a	1.83	-9.38	$2.75\cdot10^{-1}$	$2.19\cdot10^{-1}$	$2.19\cdot10^{-1}$	$2.19\cdot10^{-3}$
b	$-8.78\cdot10^{-2}$	$9.68\cdot10^{-2}$	$-4.47\cdot10^{-2}$	$-6.39\cdot10^{-3}$	$-6.39\cdot10^{-3}$	$-6.40\cdot10^{-3}$
c	$-2.62\cdot10^{1}$	$1.01\cdot10^{2}$	-5.22	-5.07	-5.07	-3.72
σ	$3.06\cdot10^{-1}$	1.35	$4.71\cdot10^{-1}$	$1.23\cdot10^{-1}$	$1.23\cdot10^{-1}$	$1.24\cdot10^{-1}$

3.2 Future wood harvest rates based on SSPs

This section shows the scenarios for future wood harvest rates in Norway until 2100 under the five different SSPs. Under SSP3, there is no or limited land-use change regulation and no participation of land-use sector and international cooperation for climate change mitigation. This SSP scenario keeps the same values of the estimated parameters $\theta_{ij} = \{a_{ij}, b_{ij}, c_{ij}, \sigma_{ij}\}, i = 1,2,3, j = 1,2,3,4$ from the historical dataset. This is thus a representation of a simple future projection of the historical trends, assuming that no major changes in policies will occur. The mean outtake volumes and market variability of the annual estimates are mainly determined by the temporal trend and the estimated population and GDP (Figure 4). The predicted mean wood harvest rates increase from 2017 and reach the maximum in 2040 with 11.9 million m^3, which corresponds to 46% of the mean annual increment of Norwegian forest. The 95% confidence interval is [9.45, 15.45] million m^3, which is equal to [37%, 60%] of the potentially available wood resources in Norway. From about 2040 onwards, the predicted mean wood harvest rate starts to decline. This can be mainly explained by the predicted decline in population under SSP3. The predicted harvested wood in 2100 is 9.49 million m^3, less than the value in 2016 and about 37% of the mean annual increment of Norwegian forests. This means that under SSP3 the forestry sector in Norway is expected to shrink in the long-term, using less than two-fifth of the potential forest resources annually available. The 95% confidence interval of the prediction in 2100 is [7.56, 12.24] million m^3, which is equal to [29%, 47%] of the potentially available wood resources. Both the annual mean and the 95% confidence interval are within the wood resource constraint of Norwegian forests. In Figure 4(b), there is a small step between 2016 and 2017. This is due to the small differences in the values for population and GDP between the SSP public database and the data from the Norwegian National statistics. The same step can be observed in the other SSP trajectories, although at a smaller extent.

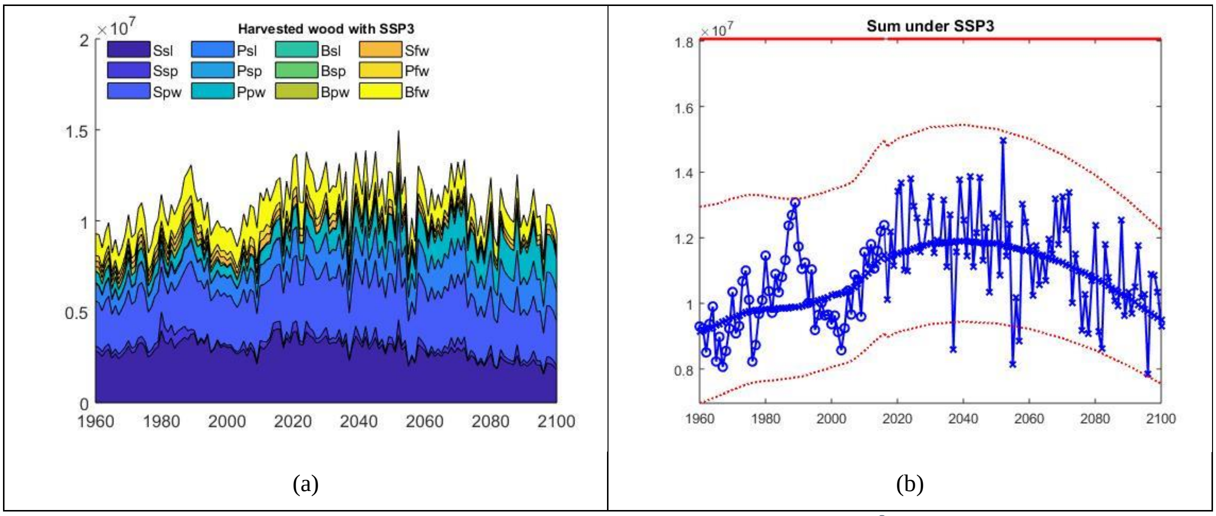


Figure 4 Predicted wood harvest rates from Norwegian forests under SSP3 until 2100 in m^3. (a) Breakdown of total outtakes per tree species and wood class (see caption in Figure 2 for the legend). (b) Trends for the total wood harvest rates. The thick blue solid line indicates the mean estimated harvested wood. The dotted lines are the 95% confidence interval of the estimated mean. The observed total harvested wood is given in blue circles and connected with solid lines. The predicted wood harvest is indicated as x with solid lines. The red solid thick line at the top is the constraint of forest resources.

Under the other SSPs, the model framework is modified using the chosen key drivers described in Table 2 with equation (2). The results are shown in Figure 5, and the predicted mean volumes of total harvested wood in 2100 together with their 95% confidence intervals for all SSPs are given in Table 4. All the predicted means except SSP5 meet the resource constraint of potential forest resources available in Norway (that is, 70% of the mean annual increment). However, all the predicted upper bound of 95% confidence intervals exceed the resources constraint, except for SSP4. With SSP1, the mean harvested wood in 2100 reaches about 68% of the potentially available wood resources, and the corresponding results for SSP2, SSP4 and SSP5 are 67%, 48% and 107%, respectively. The mean volume of the harvested wood is increased 31%, 30%, 11% and 70% for SSP1, SSP2, SSP4 and SSP5, respectively, compared to SSP3. This is the result of different degrees of participation of the land-use sector to climate change mitigation together with different trends of population and GDP. With SSP1, the harvest wood rate gradually increases and reaches the maximum in 2090 with 17.7 million m^3, and then starts to slightly decline, following the reduction in population. Under SSP4, the harvest wood rate reaches the maximum in 2070 with 13.8 million m^3 and then gradually decreases, again following population trends. In SSP2 and SSP5, the harvest wood rate increases nearly monotonically until 2100 with harvest wood rates given in Table 4. The predicted 95% confidence interval of the volumes of wood harvest rates in 2100 are [61%, 77%], [57%, 80%], [43%, 55%], [91%, 126%] of the annual increment of Norwegian wood resource for SSP1, SSP2, SSP4, and SSP5, respectively. This means that they can contribute to market fluctuations up to 16%, 23%, 12%, and 35% of the harvest potential, respectively. Compared to SSP3, the market fluctuation is reduced by 11% and 33% for SSP1 and SSP4, and increased by 28% and 94% for SSP2 and SSP5. The increase relative to SSP3 despite the reduction in σ is driven by different population dynamics. The harvest wood rates achieve the highest volumes with SSP5, where there is full participation in the land-use sector to climate change mitigation and the most significant increase of population in Norway. Results also show that the upper bound of 95% confidence intervals of the harvested wood for SSP5 is the highest among all SSPs. This is primarily due to the joint effects of all drivers. The fast growth of population and GDP together with the full participation of the land-use sector lead to a high predicted mean wood harvest rate, which is at the same time sensitive to large market fluctuations (larger than SSP1) because there is an incomplete land-use change regulation with more uncertain policies. Under SSP3 the predicted mean wood harvest is the lowest due to no or limited participation of the land-use sector, no or limited cooperation for climate change mitigation and low population. However, the upper bound of 95% confidence interval under this scenario is higher than the corresponding values for SSP1 and SSP4. This is due to limited or no land-use change regulation with SSP3, which makes market fluctuation larger, leading to effects that compensate for the higher population in SSP1 and SSP4. The upper bound of 95% confidence interval under SSP4 is the lowest due to strong land-use policies but partial participation of the land-use sector. From Figure 5, we can notice that when there is strong land-use policy (SSP1 and SSP4), the market fluctuation is smaller than the cases with incomplete land-use policies (SSP2 and SSP5) due to different rates of changes in the variance parameter of the white Gaussian noise process.

Future trends show that the mean predicted volumes of harvested wood will gradually decrease for pine as unsorted sawlog and pulpwood and birch for all kinds of wood classes except fuelwood. On the other hand, birch as fuelwood exhibit the steepest relative increase in all scenarios, followed by sawlog from pine. In particular, bioenergy from birch will increase fastest under SSP1 and SSP5, which are the most resource intensive scenarios. The future market fluctuations of each tree species and wood classes are dependent on the white Gaussian noise process with variance σ_{ijk}^{p2} for each scenario *k*, and this parameter is based on the land use policies by modifying the parameter σ_{ij}^2 according to different scenarios (given in Table 2), and the parameter σ_{ij}^2 is estimated with the historical dataset using equation (1). Therefore, given the population size, the market fluctuation is the same for all tree species and wood classes within each SSP scenario *k*, but it differs among SSPs. The different population sizes amplify the market fluctuations.

A direct comparison of the outcomes of this analysis with previous studies is challenging owing to the limited availability of perspective scenarios for the forestry sector on a country basis. In general, our estimates are in line with the major trends depicted in other studies. A recent analysis investigated the implications for global woody biomass use of achieving the 2 °C climate target in the SSP – RCP2.6 framework, and shows that stringent climate mitigation policies can favor woody biomass use for energy and sawn wood production, whereas it can inhibit mechanical pulp production (Lauri et al., 2017). This is associated with increases in average wood outtakes globally and within EU28, where the mean intensity of use of forest resources can raise from about 70% up to more than 90% by the end of the century (Lauri et al., 2017). This level of potential forest resource use is in line with our findings under SSP1. Other studies are in line with this perspective, as they generally conclude that moving from a business as usual to a high mitigation scenario would increase woody biomass outtakes and use for energy, with a stabilization or minor increases in sawn wood production and decreases in pulp wood (Raunikar et al., 2010, Favero and Mendelsohn, 2017). A similar trend is also observed when taking into account the interconnections between woody biomass material and energy uses, and the by-products in the forestry sectors (Johnston and van Kooten, 2016, Jonsson and Rinaldi, 2017, Lauri et al., 2017). Our results are based on historical regression and bottom-up detailed data of national statistics of forest species and wood classes, combined with key drivers from the SSPs and aspects for land-use sector. Other models can derive similar projections of future development of forest wood outtakes (IIASA, 2017, PIK, 2017, Havlík et al., 2012, Havlik et al., 2011, Lotze-Campen et al., 2008), although the level of detail and aggregation can differ. Future comparison with outcomes from model approaches using a top-down approach and different settings can help to understand dependencies of results on model parameterizations, characteristics, and their inherent uncertainty.

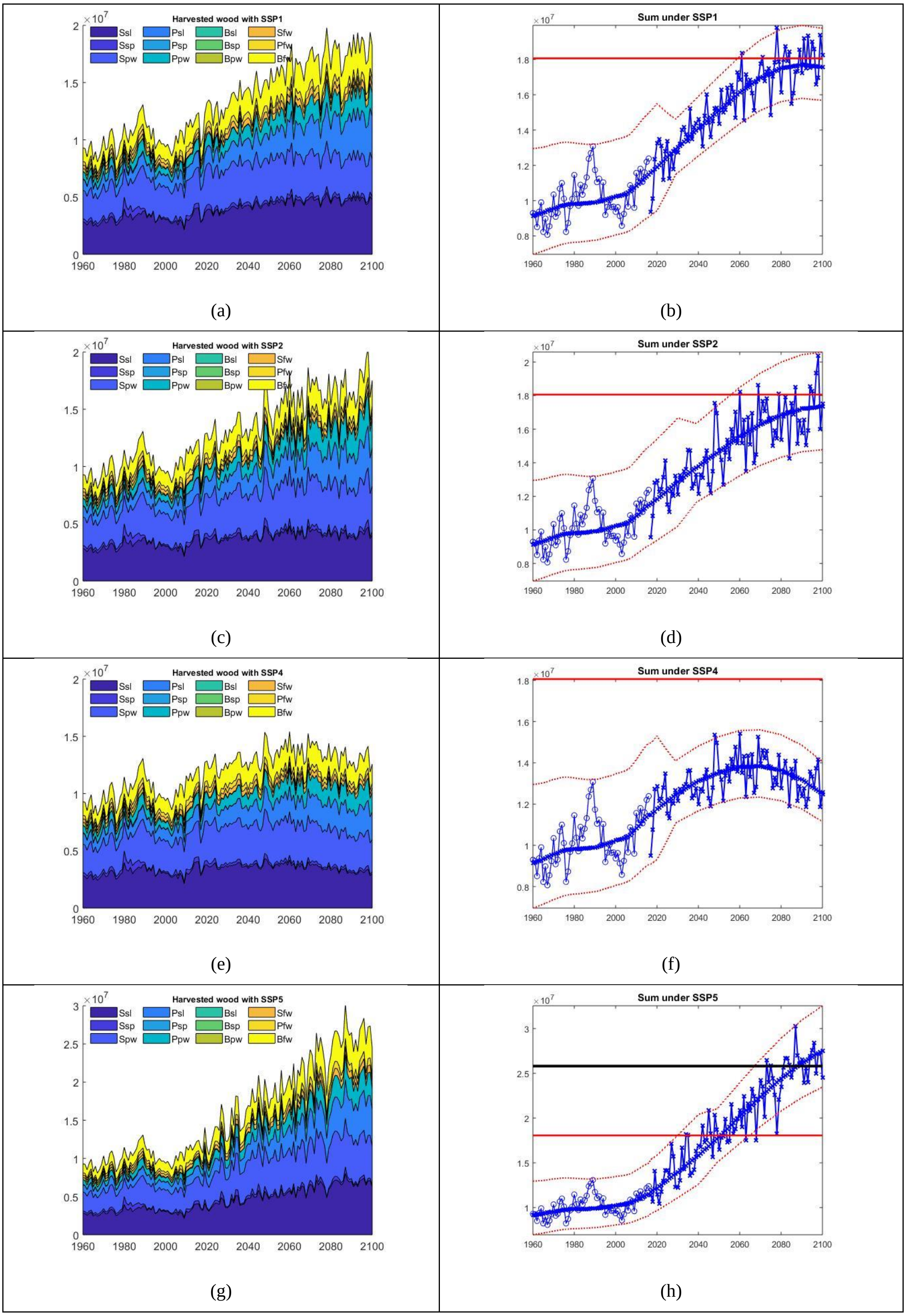


Figure 5 Predicted wood harvest rates from Norwegian forests under SSP1 (a, b), SSP2 (c,d), SSP4 (e,f) and SSP5 (g,h) until 2100 in m^3. (a, c, e, g) Breakdown of total outtakes per tree species and wood class (see caption in Figure 2 for the legend). (b, d, f, h) Trends for the total wood harvest rates. The tick blue solid line indicates the mean estimated harvested wood. The dotted red lines are the 95% confidence interval. The observed total harvested wood is given in blue circles and connected with the thin blue line. The red solid thick line is the constraint of forest resources (70% of the mean annual increment of Norwegian forests) and the solid black thick line in (h) is the mean annual increment of Norwegian forests.

Table 4 Predicted volumes of harvested wood together with their 95% confidence intervals for different SSPs in 2100 (unit: million m^3).

	SSP1	SSP2	SSP3	SSP4	SSP5
Mean	17.57	17.36	9.49	12.49	27.52
95% CI	[15.69, 19.77]	[14.78, 20.60]	[7.56, 12.24]	[11.15, 14.07]	[23.47, 32.54]

3.3 Analysis of the resource constraint

From the results above, under the model settings of the parameters given in

Table 1 and Table 2 all the predicted mean total volume of the harvest wood rates, except SSP5, do not exceed the resource constraint. Due to full participation in the land-use sector, and significant increases of population and GDP, the predicted harvest wood rates in SSP5 exceed the resource constraint and the annual maximum harvest potential. The upper bounds of 95% confidence interval of all the SSPs but SSP3 and SSP4 do not meet the resource constraint. These results show the resource constraint can become a critical parameter for future forest resource management in Norway, especially under high population and GDP growth, and increasing use of bioresources to promote the green shift to a more sustainable economy. Even though with SSP1 and SSP2 the predicted mean total volume of the harvest wood rates meet the resource constraint, there are still some chances that the wood harvest rates are too high since the upper bound of the 95% confidence intervals exceed it. Instruments to control future market fluctuations can mitigate this concern.

We further perform a sensitivity analysis of the resource constraint by introducing the factor α in equation (6), which is used to directly link wood harvest rates in SSP, either with respect to the mean or to the 95% confidence interval, to the resource constraint in Norway. There is room to increase outtake volumes for SSP1, SSP2 and SSP4, but not for SSP5 as it already goes beyond the resource constraint (in this case α needs to decrease). Results of the values of the parameter α in the different SSPs and corresponding harvest volumes are shown in Table 5. In all the cases the predicted means is adjusted to match the resource constraint of 18.06 Mm^3. In general, the lower the outtake volume in the SSP scenario the higher the value of α. With SSP1, the parameter α is $0.28\cdot10^{-3}$ and it makes the predicted maximum wood harvest rates meet the resource constraint in 2090. The maximum values of the parameter α are $0.56\cdot10^{-3}$ and $4.48\cdot10^{-3}$ in SSP2 and SSP4, respectively, and they reach the maximum wood harvest rates in 2100 and 2090, respectively. For SSP5, a negative value of the parameter is needed to shrink outtake volume down to the resource constraint. In this case, the estimated value of α is $-7.53\cdot10^{-3}$, and the maximum wood harvest ratio appears in 2080. The corresponding 95% confidence interval of these mean values are given in Table 5. In all the cases, the upper bounds of the 95% confidence intervals exceed the wood resource constraint.

When the estimate of α is based on the upper bound of the 95% confidence interval, the wood harvest rates for SSP1 and SSP2 need to be decreased, whereas they can still be increased under SSP4. With SSP1, the estimated parameter α is $-1.47\cdot10^{-3}$, and the maximum of the upper bound of the 95% confidence interval reaches the resource constraint in 2080. With SSP2, the estimated parameter α is $-2.07\cdot10^{-3}$, and the highest values of the upper bound of the 95% confidence interval occurs in 2090. In SSP4, α is equal to $2.69\cdot10^{-3}$ and the upper bound of the 95% confidence interval reaches the resource constraint in 2080. The resource constraint analysis based on the chosen threshold ϖ cannot be performed for SSP5. In this case, the upper bound of the 95% confidence interval of the wood harvest rate exceeds the resource constraint already in 2030, and it reaches 20.4 million m^3 (79% of the total harvest potential in Norwegian forests) in 2040. With equation (6), we can only start to calibrate the parameter α from 2040 onwards (the starting year of cooperation for climate change mitigation in SSP5).

In this sensitivity analysis, we assume that the mean annual increment of Norwegian forests is time-invariant, although this value is subject to changes in the future as it is sensitive to climate change, forest age class distribution, and harvest intensities under the different SSPs. Its estimation is complex as it needs to take into account the interactions among these different parameters. However, future analysis can update the resource constraint threshold, or use a dynamic resource constraint. This can be easily implemented in our modeling framework by adapting ϖ and the national mean annual increment.

Table 5 Results of wood harvest rates under the sensitivity analysis to the forest constraint (unit: million m^3) applied to either the predicted mean or to the upper bound of the 95% confidence interval. The table shows the values of α, the predicted mean of harvested wood and its 95% confidence interval for the different SSPs (SSP3 and SSP5 not shown, see text).

		SSP1	SSP2	SSP4	SSP5
Focus on	α	$0.28 \cdot 10^{-3}$	$0.56 \cdot 10^{-3}$	$4.48 \cdot 10^{-3}$	$-7.53 \cdot 10^{-3}$
mean	Mean	18.06	18.05	18.05	18.06
	95% CI	[16.11, 20.33]	[15.37, 21.42]	[16.10, 20.33]	[15.38, 21,39]
Focus on	α	$-1.47 \cdot 10^{-3}$	$-2.07 \cdot 10^{-3}$	$2.69 \cdot 10^{-3}$	n.a.
95% CI	Mean	16.03	15.21	16.02	n.a.
	95% CI	[14.30, 18.05]	[12.95, 18.05]	[14.29, 18.06]	n.a.

4 Conclusion

This study provides a model framework to link the estimates of future scenarios for a specific sector of a country with major drivers of the SSPs and aspects of the land use sector. The approach is based on a modeling framework rooted in the historical dataset and their regression models for individual items of the sector, which are then modified and extrapolated until 2100. The method is applied to the harvested wood product sector in Norway and distinguishes for each combination of species of trees and wood classes. Parameters are changed and adapted to the different SSP scenarios on the basis of key aspects like different land use regulations, participation of the land use sector and starting year of the cooperation for climate change mitigation, and are dependent on different population and GDP trends. The available wood resources are used as a constraint to calibrate model outcomes of future wood harvest rates in Norway until 2100. Population dynamics, participation rate (and timing) of the land-use sector to climate change mitigation and land-use regulation are crucial for predicting the future mean volume of harvested wood and the uncertainty of the prediction. The starting year of participation in land use sector for climate change mitigation is key to shape market fluctuations and total outtake by the end of the century. A target on either the mean volume or the upper limit of the 95% confidence interval of the harvested wood rates results in different model settings and possible resource utilization potentials.

This work is one of the first to undertake a systematic interpretation of the global qualitative SSP narratives in terms of detailed quantitative studies for a specific national sector. Outcomes of the analysis can serve as a common basis to study possible developments of the forestry sectors and their products at a Norwegian level, and their link with the SSPs make them of simple interpretation. The approach presented in this paper is easy to interpret and to be controlled, as it relies upon a bunch of simple handles. In principle, it is suitable for being applied to other sectors and countries, after the required adaption and modification. The model framework definition is independent from the characteristics of the case study and the parameters used to incorporate the key drivers of the SSPs can be adjusted on a case-specific basis. Similar approaches can help to establish a bridge between global scenarios and more narrowed analysis for individual sectors, so to reinforce the use of a consistent background setting in interdisciplinary research activities at the interface between climate systems, resources, and society, and across different spatial scales of analysis, from global to national.

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