

Assessment of MODIS NPP algorithm-based estimates using soil fertility and forest inventory data in mixed hemiboreal forests

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Abstract. Optical remote sensing data-based estimates of terrestrial net primary production (NPP) are released by different projects using light use efficiency-type models. Although spatial resolution of the NPP data sets is still too coarse (500–1000 m) for single forest stands, regional monitoring of forest management and growth with 25–100 ha sampling units is feasible if the NPP_{SAT} estimates are sensitive to forest growth differences depending on soil fertility in the area of interest. In this study, NPP estimates for 2,914 mixed forest class pixels (according to the MODIS land cover map) located in Estonia were (1) obtained from three different NPP_{SAT} products, (2) calculated using an empirical soil potential phytoproductivity (SPP) model applied to a 1:10,000 soil map (NPP_{SPP}), and (3) calculated using stem volume increment estimates given in a forest management inventory data base (NPP_{FIDB}). A linear multiple regression model was then used to explore the relationships of NPP_{SAT} with the proportion of coniferous forests, the NPP_{SPP} and distance of the pixels from the Baltic Sea coast – the variables that have been found informative in previous studies. We found a positive moderate correlation (0.57, $p < 0.001$) between NPP_{SPP} and NPP_{FIDB} . The local or downscaled meteorological data-based NPP_{SAT} estimates were more consistent with the NPP_{SPP} and NPP_{FIDB} , but the correlation with NPP_{SAT} was weak and sometimes even negative. The range of NPP estimates in NPP_{SAT} data sets was much narrower than the range of NPP_{SPP} or NPP_{FIDB} . Errors in land cover maps and in estimates of absorbed photosynthetically active radiation were identified as the main reasons for NPP_{SAT} inconsistencies.

Key words: soil potential phytoproductivity, forest inventory data, MODIS NPP, fAPAR, land cover maps.

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Introduction

Productivity of forest ecosystems is monitored and estimated using terrestrial sampling e.g. in case of National Forest Inventories (Tomppo *et al.*, 2010; GFOI, 2013; Bontemps & Bouriaud, 2014) or forest growth monitoring networks (Sims *et al.*, 2014; Kiviste *et al.*, 2015), using airborne lidar (ALS) data (Kandare *et al.*, 2017), process-based modelling (Liu *et al.*, 1997), combining ALS data and climate data with process-based modelling (Härkönen *et al.*, 2013) or using spaceborne measurements of absorbed photosynthetically active radiation (APAR) in light use efficiency models (Zhao *et al.*, 2005) as an alternative to pure terrestrial sampling. The light use efficiency or (LUE)-type models estimate the gross primary production of photosynthesis (GPP) based on APAR, LUE, water vapour pressure deficit (VPD) and ambient air temperature. Net primary production (NPP) is calculated by subtracting autotrophic respiration from the GPP. Such models are used routinely for terrestrial net primary production NPP_{SAT} estimates based on global satellite measurements (Zhao *et al.*, 2011). The estimates have been validated e.g. using eddy-covariance measurements from flux towers (Turner *et al.*, 2006) and ground reference NPP (Olson *et al.*, 2001). Locally at specific sites, however, the estimates may have large uncertainties due to errors in model parameters and assumptions (Zhao *et al.*, 2005), coarse scale input data (Eenmäe *et al.*, 2011) and errors in land cover maps (Quaife *et al.*, 2008; Lang *et al.*, 2013). Higher accuracy could be achieved by using local or downscaled meteorological data (Olofsson *et al.*, 2007; Härkönen *et al.*, 2010; Nilson *et al.*, 2012; Neumann *et al.*, 2016) and combining remote sensing data and sample plot-based forest inventory data (Härkönen *et al.*, 2011).

The growth of plants is determined by soil fertility in addition to APAR and ambient conditions (Tooming, 1977). More

fertile soil stipulates photosynthesis. Waring *et al.* (2006) showed that soil fertility at a coarse scale is strongly correlated with the multispectral enhanced vegetation index which is a good predictor for GPP (Schubert *et al.*, 2012). Inclusion of soil data into global scale NPP estimation models is problematic due to generality and inconsistencies of the existing global soil databases e.g. the harmonized world soil database, HWSD (FAO *et al.*, 2012). However, high quality soil maps can be a valuable data source for evaluation of spaceborne NPP estimates when information for soil productivity estimation is available in the soil data base, on the other hand, soil management (Kölli & Kanal, 2010) may benefit from satellite data-based yearly estimates of the NPP. Discrepancies between NPP_{SAT} and the potential productivity of soil can be used for targeting the areas where the forest management practices have to be reviewed. Time series of the NPP_{SAT} are found informative for tree mortality monitoring and predicting (Neumann *et al.*, 2017). Regional monitoring systems e.g. sCASE (Stagakis *et al.*, 2015) can be constructed to locate problematic areas based on NPP_{SAT} . A necessary prior for this type of monitoring application is the evaluation of relationships between NPP_{SAT} estimates and soil productivity in the area of interest.

In this study, we analysed LUE-based estimates of NPP_{SAT} to evaluate their possible applicability in a forest NPP monitoring system in Estonia. We were interested in finding the most critical error sources in the NPP_{SAT} estimates that must be targeted in future research. The NPP_{SAT} was calculated from GPP, if available, using a uniform NPP/GPP ratio to decrease uncertainties arising from leaf area index (LAI) estimates and averaged over observation period. To carry out the study, we constructed a GIS database where the elementary sampling unit (ESU) was a MODIS grid cell with the size of 50 ha. Considering that the mean forest stand size in Estonia is about 1.3 ha (Raudsaar *et al.*, 2016) we used

data from mixed forest class ESUs. Since there is only one flux tower in Estonia (Noe *et al.*, 2015) where continuous measurements are done, we used the soil potential phytoproductivity (SPP) model of Kõlli (1988) applied to the database of a 1:10,000 soil map as an independent reference for the assessment of NPP_{SAT} . To each ESU we assigned also (1) tree species composition, site index and an estimate of NPP based on stem volume increment from a forest inventory database (FIDB) (2) an estimate of disturbed area and current forest land area from Landsat images-based map, (3) land cover class codes from MODIS land cover maps, (4) fraction of APAR (fAPAR) from MODIS and MERIS products that were used, and (5) distance from the Baltic Sea coast. We used regression modelling to analyse the relationships between the long term mean NPP_{SAT} and the explanatory variables in the database.

Material and Methods

Soils of Estonia

Located in the transition area between continental and marine climates in mild and wet pedo-climatic conditions of the temperate zone, mixed forests are characteristic of the naturally developed areas of the Estonian land cover. In the course of intensified agricultural activity during the last two centuries the most productive soils (suitable for crop cultivation and grasslands) were turned into arable, pastured or hay-lands.

At present the forests cover approximately half of the Estonian land surface (Raudsaar *et al.*, 2016). A remarkably large part (36.9%) of forest soils form *Histosols* (classification system: IUSS (2014)), whereas among them *sapric* and *fibric* soil subdivisions in fens and bogs are dominating. The *Gleysols* form approximately 35.7% of forest soils, while half of them are characterized as *eutric* (calcareous) and a quarter as *dystric*. Also *Histic Podzols* belong to this

wet (*epigleyic*) mineral soil group (forming ~3% of forest soils). The share of automorphic mineral soils is only 24.3% of forest: subdivisions of *Retisols* (7.9%), *Cambisols* (6.5%) and *Podzols* (6.0%) are dominating (Kõlli *et al.*, 2009).

The dominating texture of forest soils is peat (37%) and sand (35%). The share of loams, which have the highest forest growing potential, is only 16% of the forest land. The share of loamy sands and clays is 9% and 3%, respectively, of the forest land. With respect to moisture conditions 39% of forest soils are characterized as wet mineral (*epigleyic*), 37% – wet peaty (*histic*), 13% – automorphic fresh, 9% – moist (*endogleyic*) and 2% – dry, aridic.

Soil map and database

The results of preliminary soil survey of Estonia from 1954 to 1980 are large scale (1:10,000) soil maps and the corresponding database (Mullakaardi, 2001). The map covers entire terrestrial territory (43,432 km²) of the Estonia. Later, these maps have been updated paying more attention to the fabric of humus profiles, particle size distribution, organic carbon and nitrogen content, and the main chemical and physical properties of topsoil. In 1998–2001 the large scale soil map of Estonia was digitised by E.O. Map Ltd for reproduction of hardcopies of the map. This soil map is the property of the Estonian Land Board (Mustamäe tee 51, 10621, Tallinn, Estonia). The database contains soil codes, formulae of soil texture and humus profiles, stoniness, soil quality and relative share of soil subtypes within complex soil polygons. The percentages were used as weights for the mean productivity for each soil polygon.

Model of soil phytoproductivity

For characterizing the SPP the pedo-ecological schema of normally developed mineral soils (i.e. soils which, at present, are not influenced by new sediments accumulation nor topsoil elimination) was used (see Figure 2 in Kõlli *et al.*, 2004). This

schema categorizes soils according to their pedo-ecological conditions. It is characterized by two scalars: (1) a vertical eight-stage litho-genetic scalar from rendzina to podzols, which arranges soils on the basis of parent materials' properties, calcareousness, processes of soil functioning and site trophicity, and (2) a horizontal six-stage moisture scalar from aridic or well-aerated to permanently wet or reducing conditions. To estimate potential productivity for each soil in the soil map data base we used a simple model (Kölli, 1988) which in principle is a look-up table relating the two scalars and above-ground SPP. No other input is required for the model.

The plant biomass measurement data-based semi-empirical SPP model (Kölli, 1988) was initially created for quantitative characterization of organic matter (organic carbon) flux throughout the soil, which started with litter fall on the surface and subsequent phytomass transfer into the soil. As litter fall depends on plant cover productivity, the long period mean annual SPP ($\text{Mg ha}^{-1} \text{ yr}^{-1}$) for the main soil types had to be estimated. Two substantial aspects have to be mentioned: (1) soil productivity comprises not only the productivity of the plant cover (primary or phytomass productivity), but also the biomass productivity of meso- and microfauna, which is negative in relation to primary (phytomass) productivity, and (2) the mean annual SPP level was determined in relation to stabilized forest ecosystems when the tree storey has passed the fastest growing period, but the understory layers have stabilized. The forests in the phytomass sampling sites had (1) the stand relative density in the range of 0.6–0.8, and (2) the mean age of stands in the range of 60–100 years (Kölli, 1988).

The above reveals that (1) in earlier growing periods of spruce, pine, birch, etc. forests the total annual SPP can be remarkably greater than estimated with our SPP model, and (2) the annual SPP is always smaller than the annual NPP ($\text{SPP} < \text{NPP}$),

which is caused by secondary productivity and heterotrophic respiration (i.e. decay of attached dead branches) of the plant cover. Therefore the SPP may be treated as a persisted (or survived) NPP at the end of the vegetation period. However, we assume that SPP characterizes adequately the differences in productivity between different soil types.

Estimation of soil potential NPP

The SPP model was taken from Figure 3.2 in Kölli (1988), digitized and converted into a 80×80 units lookup table. The lookup table was based on soil genetic and moisture coordinates which were also assigned for each soil patch in the soil database. The original SPP model was based mainly on empirical data from normally developed soils and estimates the potential above-ground phytoproductivity (P_{SPP}). For waterlogged *Gleysols* and thin *Sapric Histosols* (M') with characteristic horizons of the forest floor, raw-humus and peat indicating to stagnated growth conditions, an adjustment based on the thickness of these layers was applied

$$P_{\text{SPP(G)}} = P_{\text{SPP}} - g (O_{\text{HOR}} - \bar{O}_{\text{HOR}}) \quad (1)$$

where O_{HOR} is the total thickness (cm) of the layer of organic matter and peat, $g = (P_{\text{SPP}}(\text{Go}) - P_{\text{SPP}}(M'))/40 = 0.12$ is a parameter based on $P_{\text{SPP}} = 12.9 \text{ Mg ha}^{-1} \text{ yr}^{-1}$ for *Mollic Gleysols* (Go) and $8.2 \text{ Mg ha}^{-1} \text{ yr}^{-1}$ for M' soil and their 40 cm difference in O_{HOR} , and \bar{O}_{HOR} is the mean O_{HOR} for each soil type in the soil database. An additional adjustment $P_{\text{SPP(GI)}} = 0.85 \times P_{\text{SPP(G)}}$ was applied to *Luvic Gleysols* (GI) based on clay, sand or fine sand.

LUE-type models estimate the total product of photosynthesis, i.e. above and below-ground. We scaled $P_{\text{SPP}} \times (1+0.2) = \text{NPP}_{\text{SPP}}$ to add an estimate of below-ground NPP to the model of Kölli (1988). The factor 1.2 corresponds to IPCC (2006) guidelines for mature stands in the temperate forest zone. The factor 1.2 here also counts

for fine root turnover, since the SPP model includes litter fall which can be assumed similar to fine root turnover according Raich & Nadelhoffer (1989).

Forest management inventory database and calculation of stem volume increment-based NPP

The forest management inventory database (FIDB) was obtained in March 2013 from the State Register for Accounting of Forest Resource (IDB, 2016). The FIDB records are yearly updated only for state forests and the age of the inventory records is usually not more than five years, whereas data for private forests may be outdated, since updates are not obligatory after disturbances including management. The FIDB consists of a 1:10,000 vector map of forest stands and a large set of stand specific inventory variables used for forest management planning issues. In this study, we used site fertility index H_{100} (m; predicted height when forest is 100 years old) and tree species composition as descriptive variables and stem volume increment i_v ($\text{m}^3 \text{ha}^{-1} \text{yr}^{-1}$) to estimate NPP. The i_v in the FIDB is used for forest management planning and is calculated with a model (Metsakorralduse, 2017) using forest age, stand relative density and H_{100} . The net primary production $NPP_{\text{FIDB}} = i_v \times BCEFi + 2 \times m_L$ for each forest stand was calculated by using the biomass conversion and expansion factor $BCEFi = 0.6 \times (1 + 0.2) = 0.72$ and yearly litter fall m_L . The $BCEFi$ was derived from IPCC (2006) guidelines for mature stands in the temperate forest zone and includes also the below-ground fraction. The fine root turnover was assumed to be equal to litter fall according to Raich and Nadelhoffer (1989).

The yearly litter fall m_L ($\text{g m}^{-2} \text{yr}^{-1}$) was estimated with a temperature (T) and precipitation (S) driven model from Liu *et al.* (2004) for deciduous broadleaf forests

(2)

$$m_{L(\text{dec})} = \exp(2.643 + 0.726 \times \ln(T+10) + 0.181 \times \ln(S))$$

and evergreen coniferous forests

(3)

$$m_{L(\text{con})} = \exp(2.708 + 0.505 \times \ln(T+10) + 0.24 \times \ln(S))$$

where $T = 5.1^\circ \text{C}$ and $S = 700 \text{ mm yr}^{-1}$ were used as climatological mean values for Estonia (Kliimaatlas, 1970).

Satellite data-based NPP estimates

Three data sources were used to obtain annual estimates of NPP_{SAT} . First was a Terra MODIS (Moderate-resolution Imaging Spectroradiometer) data-based GPP | NPP product (version 5.5) released by the Numerical Terradynamic Simulation Group (NTSG; The University of Montana, USA). The GPP and NPP values are based on yearly reprocessed data to decrease the influence of missing data due to clouds (Zhao *et al.*, 2011; Zhao *et al.*, 2005). The second NPP_{SAT} estimate was extracted from MODIS EURO product (Neumann *et al.*, 2016) and was also based on Terra MODIS data but using downscaled European climate data (Moreno & Hasenauer, 2016) instead of the global climate driver. The third productivity estimate was based on Envisat MERIS data and is described in more detail by Nilson *et al.* (2012) who developed a LUE-type model EST_PP. The EST_PP model was run using high spatial resolution meteorological data and a local land cover map (Nilson *et al.*, 2012).

In this study we preferred the NPP_{SAT} estimates derived directly from the GPP, if available, instead of using LAI-based autotrophic respiration-based NPP_{SAT} . A simple scaling with a uniform ratio was applied to avoid errors inherent in LAI estimates and combined effects of land cover map-based model parameters.

The EST_PP GPP and NTSG MODIS GPP were converted to NPP using the ratio of MODIS NPP/GPP=0.55 for mixed forests taken from Nilson *et al.* (2012). This factor is greater than that presented by Zhao *et al.* (2005) who show also a smaller NPP/GPP for deciduous broadleaf forests

compared to evergreen coniferous forests. We also tested NPP/GPP ratio weighting with the share of coniferous trees according to the FIDB, since the share of coniferous stands in our 50 ha sampling units varies. The EST_PP-based $NPP/GPP = 0.66$ was used for deciduous broadleaf forests and $NPP/GPP = 0.45$ for evergreen coniferous forests (Table 2 in Nilson *et al.*, 2012). In total we had five estimates of NPP_{SAT} (Table 1) from the period of 2000–2012. Average value over the period of each NPP_{SAT} estimate was used, since the soil fertility-based NPP_{SPP} corresponds to a long term average value.

Table 1. Description of NPP and fAPAR estimates used in this study.

Tabel 1. Taimkatte primaarse produktsiooni ja fAPAR hinnangud.

Variable / Tunnus	Data source and description / Kirjeldus ja viited
NPP_{SPP}	Soil potential NPP based on the soil map and model of Kölli (1988)
NPP_{FIDB}	Stemwood volume increment scaled by the <i>BCEFi</i> plus an estimate of litter and production of fine roots (2, 3) according to tree species composition
NPP_{NTSG_GPP}	NTSG MODIS GPP (Zhao <i>et al.</i> , 2011) scaled using a 0.55 NPP/GPP ratio
NPP_{NTSG}	NTSG MODIS NPP (Zhao <i>et al.</i> , 2011)
$NPP_{EST_PP_GPP}$	EST_PP MERIS GPP (Nilson <i>et al.</i> , 2012) scaled using a 0.55 NPP/GPP ratio
$NPP_{EST_PP_GPP_SW}$	EST_PP MERIS GPP (Nilson <i>et al.</i> , 2012) scaled using tree species' weighted NPP/GPP ratio
NPP_{EURO}	MODIS EURO NPP (Neumann <i>et al.</i> , 2016)
$fAPAR_{ME}$	mean yearly (from April to October) sum of MERIS fAPAR
$fAPAR_{MO}$	mean yearly (from April to October) sum of MODIS fAPAR

Data analysis

Data analysis was carried out in a grid similar to the Climate Modeling Grid used for MODIS products (Figure 1). The geographical coordinate system (latitude, longitude) was used. In Estonia the size of the grid pixels in a Cartesian coordinate system is about $1,000 \times 500$ m. Spatial queries in the GIS were carried out to assign mean attribute values from all input data sets to the grid pixels. Since the landscape in Estonia is heterogeneous with respect to the $1,000 \times 500$ m sampling units and there are errors in raster data due to resampling in coordinate system transformation, only the pixels located at least 1 km inside forest patch borders were extracted. This was to decrease errors inherent from raster image resampling, gridding effects in MODIS images (Tan *et al.*, 2006) and the influence of view geometry (Xin *et al.*, 2013).

The FIDB stand map provides spatially continuous information on forests and analyses can be carried out using individual pixels of the MODIS grid (Figure 1) instead of aggregating the pixels by at least 0.066° resolution as found appropriate for sample plot-based National Forest Inventory data by Moreno *et al.* (2016). To exclude pixels with outdated forest inventory data we used disturbance maps based on Landsat images (Urmas Peterson, Tartu Observatory, personal communication). The Landsat dataset covers the period of 1987–2013 with about a five-year interval.

For the analysis we extracted pixels located more than 30 km away from the Baltic Sea coast to avoid artefacts caused by the VPD in LUE-type models in the Baltic region (Eenmäe *et al.*, 2011; Lang *et al.*, 2013). Next, the pixels which had a forest inventory data cover less than 75% of their area were eliminated from the evaluation. Finally, by selecting the pixels with less than 10% of the pixel area disturbed since 2001 and after removing 84 outliers, the total number of mixed forest class pixels according to the MODIS land cover map (MCD12Q1, UMD (Type 2), year 2001) was

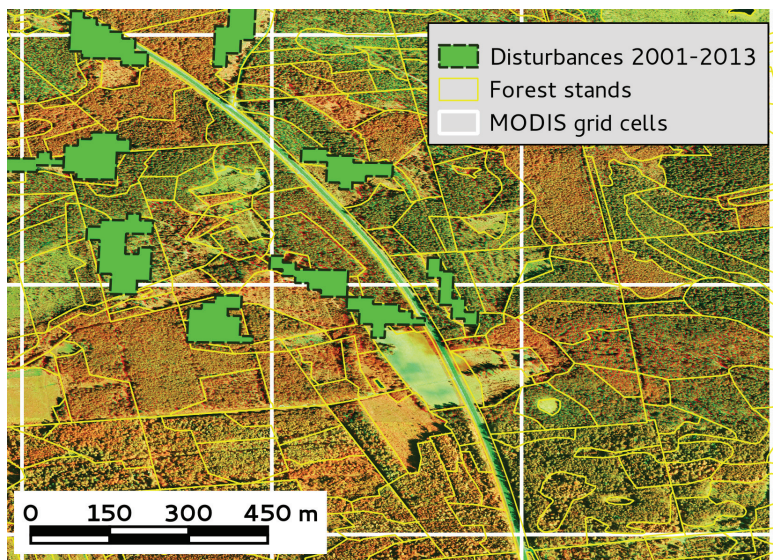


Figure 1. A fragment of the MODIS grid showing borders of six sampling units. Each MODIS grid cell was assigned information from reference data sets.

Joonis 1. Igale vaatlusühikuna kasutatud MODIS võrgustiku piksile arvutati puistute keskmised takseertunnused ja keskmine mullaviljakus. Taustal on väärvärv ortofoto.

2,914, which corresponds roughly to 1,340 km².

The factor $c_f = 0.5 \text{ g C g}^{-1}$ was used as the fraction of carbon in biomass for NPP_{SPP} and NPP_{FIDB} which were based on biomass estimates.

To analyse NPP and fAPAR estimates given in Table (1) we used a linear regression model

$$y = a_0 + a_1 Z_{DAO} + a_2 NPP_{SPP} + a_3 K + \beta, \quad (4)$$

where a_x are parameters, Z_{DAO} indicates the global coarse spatial-scale meteorological data-caused longitudinal zones (Eenmäe *et al.*, 2011) in NTSG MODIS NPP_{SAT} estimates, K (%) is the percent of coniferous trees (forests) calculated from FIDB and β is the error term. The value $Z_{DAO} = 2$ was used for central Estonia (longitude 24.4°–26.5° E) and $Z_{DAO} = 3$ for the Eastern part of Estonia. The number of observations was 2,914.

Results and Discussion

Forest structure in the elementary sampling units

When the MODIS grid cells were used as observations the interquartile ranges of forest age, canopy cover (describes stand density) and the share of coniferous forests were 37–58 years, 53–70% and 31–69%. In most of the ESU-s the mean age of forests is less than was in the sample forests used for the SPP model, but the difference is not large. For this analysis we selected mixed forest class pixels from NPP_{SAT} datasets according to MODIS land cover map. According to the forest inventory data only half of the sample corresponds do the definition indicating problems in the MODIS land cover map.

Ground data-based NPP estimates

Soil data-based NPP estimates were first compared to the forest site index of the FIDB and NPP_{FIDB} (Figures 2 and 3). As expected, the forest site index H_{100} was

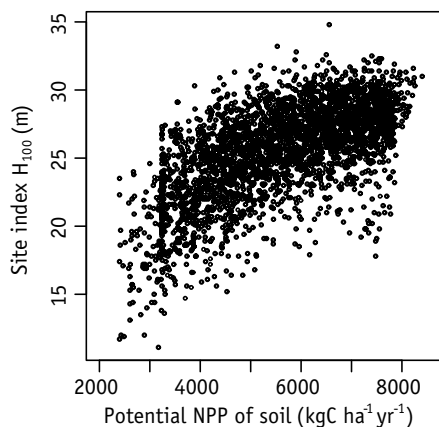


Figure 2. Forest inventory-based site fertility index and soil potential NPP.

Joonis 2. Boniteet ja mulla potentsiaalne füto-produktiivsus.

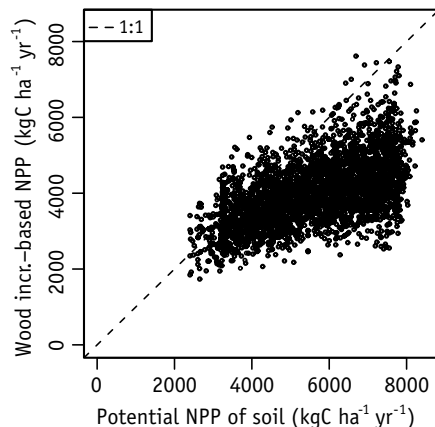


Figure 3. Wood volume increment-based NPP of trees and soil potential NPP.

Joonis 3. Tüvepuidu juurdekasvu järgi hinnatud puistu NPP ja mulla potentsiaalne füto-produktiivsus.

positively correlated ($0.63, p < 0.001$) with the NPP_{SPP} showing that the two terrestrial data sets are not conflicting. The NPP_{SPP} described 28% of the wood volume increment-based NPP estimate in a simple linear regression model. The mean value of NPP_{SPP} ($5.6 \text{ tC ha}^{-1} \text{ yr}^{-1}$) was greater ($p < 0.001$) than NPP_{FIDB} (Table 2) and the interquartile range of NPP_{SPP} was also larger ($2.34 \text{ tC ha}^{-1} \text{ yr}^{-1}$). It is not clear how well the factor 1.2 covered fine root production for NPP_{SPP} . The mean value of fine root production as estimated with model of Liu *et al.* (2004) for the Estonia corresponded to $1.5 \text{ tC ha}^{-1} \text{ yr}^{-1}$ which is similar to the mean value for temperate zone as reported by Finér *et al.* (2011) who show also a large variability of the estimate. Another reason for the difference is that we accounted only for the tree layer in NPP_{FIDB} ignoring forest understory (regrowth, bushes, grass, mosses and lichens). However, in dense forest stands the relative share of forest understory in the total biomass production is small (Varik *et al.*, 2009). Discrepancies between NPP_{SPP} and NPP_{FIDB} are also caused by the underestimation of stem volume increment by the model used in forest management inventory according to a recent vali-

dation on repeated measurements of the Estonian National Forest Inventory sample plots (Allan Sims 2017, The Estonian Environment Agency, personal communication). The correlation between NPP_{SPP} and NPP_{FIDB} could also be improved by using stand-specific biomass expansion factors. However, the relationships provide enough evidence that NPP_{SPP} can be used to evaluate LUE-type model-based NPP_{SAT} estimates, since the soil map covers whole of Estonia and the SPP model was based on biomass sampling data including litter fall.

There was a characteristic lack of fit of the LUE-based NPP_{SAT} along the soil fertility gradient (Figure 4a, 4b). To some extent the lack of fit can be related to fine root production which was assumed to be a constant proportion of above-ground NPP in NPP_{SPP} . The estimates of fine root production vary with different methods (Yuan & Chen, 2012a). The amount of fine roots depends on forest age and understory (Makkonen & Helmisaari, 2001). In fertile middle-aged spruce stands fine root production can be 13% of the total NPP (Ostonen *et al.*, 2005). Fine root production tends to increase with soil fertility (Yuan & Chen, 2012b), but in less fertile soils plants

have to invest relatively more of the total NPP in their root system (Vanninen & Mäkelä, 1999). However, fine roots cannot explain the about three times smaller interquartile range of LUE-based NPP_{SAT} estimates compared to NPP_{SPP} (Table 2).

The influence of applied NPP/GPP ratio on the NPP_{SAT} estimates

The small variability in the LUE-based NPP_{SAT} of the sample can be caused to some extent by the constant NPP to GPP ratio that was used to calculate the NPP from GPP. This approach is similar to the production of global-scale LUE-based NPP estimates where one set of model parameters is used for the mixed forest class. In mixed forests, however, the NPP/GPP is related to the species composition and mainly to the ratio of evergreen coniferous and deciduous broadleaf tree species. Based on MODIS GPP and NPP estimates Zhao *et al.* (2005) give $NPP/GPP = 0.35$ for deciduous broadleaf forests and 0.54 for evergreen coniferous forests. DeLucia *et al.* (2007) show that

in the temperate climate zone the NPP/GPP ratio is just the opposite. The NPP/GPP ratio depends also on stand age (Mäkelä & Valentine, 2001; Tang *et al.*, 2014), however, considering the mean stand size of 1.3 ha in Estonia (Raudsaar *et al.*, 2016) and the 50 ha observation units used in this study the age-dependent effects are probably not prevailing over the tree species-dependent influence on the NPP/GPP.

The share of coniferous forests was significant in the model (Eq. 4). By excluding K from the model (Eq. 4) the variability described (R^2) by the constant NPP/GPP-based $NPP_{EST_PP_GPP}$ decreased from 0.30 to 0.19. When K was used as the weight to convert the EST_PP GPP to $NPP_{EST_PP_GPP_SW}$ the model (Eq. 4) excluding K still described 27% of variability in $NPP_{EST_PP_GPP_SW}$ and also the range of NPP values increased (Table 2). The reason here is negative correlation ($-0.47, p < 0.001$) between the share of evergreen coniferous forests in our individual observations and soil potential NPP. Poor soils in Estonia are usually dominated by

Table 2. Parameter estimates for the multiple linear regression model Equation (4). Dependent variables are described in Table (1). The IQR is the interquartile range of the NPP estimates. Statistically non-significant values are in italics.

Tabel 2. Regressioonimudeli võrrandi (4) parameetrite hinnangud. Statistiliselt mitteolulised väärtused on kursivis. Funktsioontunnused on kirjeldatud tabelis (1). IQR on kvartiilhälve.

Dependent variable / Sõltuv muutuja	Mean / Keskväärts (kg C ha ⁻¹ yr ⁻¹)	IQR	Model parameters / Mudel parameetrid				
			a_0	a_1	a_2	a_3	R^2
NPP_{FIDB}	4020	1124	235*	293	0.29000	-2.17	0.32
NPP_{NTSG_GPP}	5512	362	5869	-215	0.00570	2.97	0.21
NPP_{NTSG}	5451	491	6171	-371	-0.00630	4.88	0.43
NPP_{NTSG}	5451	491	5234	-	-0.01100	5.56	0.16
$NPP_{EST_PP_GPP}$	4429	171	4358	20	0.02200	-2.06	0.30**
$NPP_{EST_PP_GPP_SW}$	4472	749	3306	85	0.17000	-	0.27
NPP_{EURO}	5260	302	4878	107	-0.02300	4.91	0.39
$fAPAR_{ME}$	-	-	175	-1.35	0.00049	-0.042	0.14
$fAPAR_{MO}$	-	-	154	1.68	0.00004	0.032	0.03

* the NPP_{FIDB} for parameter estimation was without the litter and fine roots to avoid artificial correlation with the species composition variable (K) used also as weight for litter model equations (2, 3).

** $R^2 = 0.19$ when the share of coniferous forests was excluded from the model argument list.

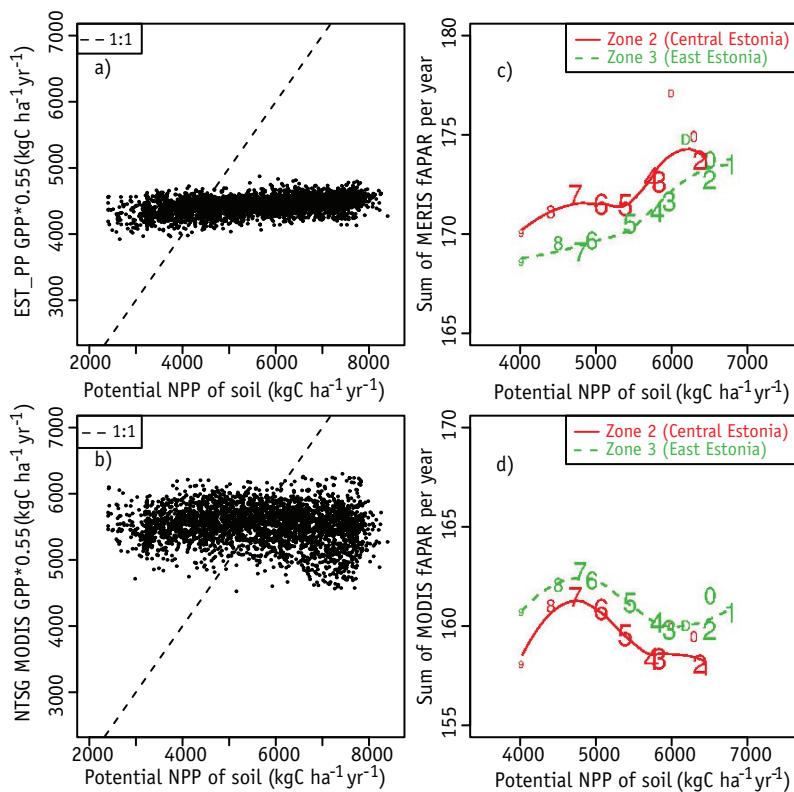


Figure 4. LUE-based NPP_{SAT} estimates (a, b; see Table 1) depend more on $fAPAR$ (c, d) than on the potential NPP of the soil. Numeric symbols correspond to the proportion of evergreen coniferous forests, “D” stands for 100% deciduous broadleaf forest class, and symbol size corresponds to the number of pixels.

Joonis 4. LUE-mudelil põhinevad NPP hinnangud ei reageeri oluliselt mulla viljakusele Eestis (a, b), vaid neid mõjutab pigem mudeli sisendiks olev $fAPAR$ (c, d). Numbersümbolid näitavad okaspuude osakaalu, „D” tähistab 100% lehtpuumetsa klassi. Sümbolid on skaleeritud vastavalt pikslite arvule klassis.

Scots pine except in lowland fens where black alder and downy birch are the prevailing species. With the increase in soil fertility the share of Norway spruce increases on account of Scots pine and deciduous dominated mixed forests are in majority (Adermann, 2009). A weak negative correlation (-0.31 , $p < 0.001$) exists also between the share of coniferous forests and stem volume increment estimates in the pixels.

Evaluation of the NPP_{SAT} estimates

By using the parameters from Table (2) of the model Eq. (4) for NPP_{FIDB} as a reference the LUE-based NPP estimates can be analysed. Similarly to NPP_{FIDB} the EST_PP NPP

estimates had a positive correlation with the longitude of pixel position as well as with the SPP, but correlation with K was negative. The NPP estimate (NPP_{NTSG}) from the standard global product had a negative correlation with the pixel position longitude which is a similar relationship to that found by Eenmäe *et al.* (2011) for the MODIS product. The correlation of NPP_{NTSG} with NPP_{SPP} was not significant and correlation between NPP_{NTSG} and K was positive which is the opposite of the correlation found with NPP_{FIDB} . By excluding the variable Z_{DAO} from the model, only 16% of variation of NPP_{NTSG} was described compared to the initial 43% (Table 2).

The MODIS data and downscaled meteorological data-based NPP_{EURO} had a positive correlation with the pixel location longitude similarly to NPP_{FIDB} which indicates successful use of European downscaled climate data by Neumann *et al.* (2016). Although the relationship with NPP_{SPP} was negative and significant in the model, NPP_{SPP} described only 2% of the variation in NPP_{EURO} . For comparison: when only K was included in the model (Eq. 4) still 32% of variation in NPP_{EURO} was described, but the correlation was positive, i.e. opposite to the correlation between NPP_{FIDB} and NPP_{SPP} and also between NPP_{SPP} and EST_PP -based NPP. NPP_{EURO} was calculated from the GPP by subtracting autotrophic respiration and growth losses based on the LAI (Neumann *et al.*, 2016). The problems must therefore be looked for in LAI estimates or in fAPAR which strongly correlated ($R^2 > 0.43$) with the derived NPP_{SAT} in all the corresponding Envisat MERIS and Terra MODIS data-based estimates.

The estimates of the fraction of absorbed photosynthetically active radiation

The model (Eq. 4) described 14% of $fAPAR_{ME}$ but only 3% of $fAPAR_{MO}$ variability (Table 2). The relationship between NPP_{SPP} and $fAPAR_{ME}$ was close to linear, but with $fAPAR_{MO}$ the relationship was nonlinear with the shape somewhat depending on the proportion of evergreen coniferous forests in the pixels (Figure 4c, 4d). It also appears that fAPAR from MERIS and MODIS have the opposite correlation with pixel location longitude (Table 2) and also with the share of evergreen coniferous forests in the pixels. However, the models describe only a small part of fAPAR variability and a fAPAR targeted study based on an independent reference measurement of fAPAR is required to explain the co-relations. For example, Kuusk *et al.* (2016) found that landscape albedo from MODIS data is underestimated due to small clouds which can have similar effect on the fAPAR measured using coarse spatial resolution sensors.

Land cover maps as the source of errors

D'Odorico *et al.* (2014) found that the differences between MODIS and MERIS fAPAR products may be related to land cover maps used for determining radiative transfer model parameters from look-up tables or the assumptions made for the estimation procedure. Errors in land cover types influence GPP estimates through fAPAR estimates. Wrong light use efficiency factors and growth limiting functions influence also NPP estimates. For example, for NPP_{NTSG} and MODIS fAPAR different land cover maps are used – Type 2 and Type 3.

We extracted a set of pixels with a big productivity potential ($NPP_{SPP} > 5 \text{ t C ha}^{-1} \text{ yr}^{-1}$) and a small yearly sum of $fAPAR_{MO}$ and found that the mixed forests according to the MODIS Type 2 land cover map belong to the class “Evergreen Needleleaf forest” in the Type 3 land cover map and according to the ground truth data from the FIDB there are deciduous broadleaf-dominated forests. With another query a set of pixels with the biggest $fAPAR_{MO}$ was extracted along the NPP_{SPP} range. In the Type 3 land cover map the pixels belonged to the “Evergreen Broadleaf forest” class which does not exist in Estonia. According to orthophotos and the FIDB the pixels were from pine stands in transitional sphagnum bogs or coniferous dominated forests. There is no mixed forest class in the Type 3 land cover map. The 2,914 mixed forest class pixels in the Type 2 land cover map were distributed between the “Evergreen Broadleaf forest” (172), “Deciduous Broadleaf forest” (454) and “Evergreen Needleleaf forest” (2,288) classes in the Type 3 land cover map. While the EST_PP NPP estimates were based on local land cover maps and were in agreement with the FIDB data and SPP, similar improvements can be expected in the MODIS GPP|NPP when thematically more accurate land cover data is used.

Conclusions

The Estonian soil map and forest management inventory database provided valuable information for evaluation of satellite data-based NPP estimates. The two terrestrial estimates showed smaller NPP for poor soils and greater NPP for fertile soils. This was in contrast to the LUE-type model estimated NPP that had mean value similar to the terrestrial estimates, whereas almost no reaction to change in soil fertility in Estonia. The main reason for the lack of fit was apparently the estimate of fraction of absorbed photosynthetically active radiation which is the main input variable of LUE-type NPP models. A validation of the Type 2 land cover map showed that classification of 50% of the mixed forest class pixels is not correct. Land cover maps are used in the estimation of fAPAR and NPP. Improved land cover maps following the classification schema of the current global maps can be constructed regionally by local institutions that have access to high resolution data (both thematically and spatially). Subsets of the global land cover maps could then be updated to obtain more consistent fAPAR, GPP and NPP estimates locally and globally. We also see a need for improved methods for the fAPAR estimation for hemiboreal mixed forests.

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References

- Adermann, V. 2009. Forests of Estonia. (Eesti Metsad 2008). Metsakaitse- ja Metsauuenduskeskus, Tallinn. (In Estonian).
- Bontemps, J.D., Bouriaud, O. 2014. Predictive approaches to forest site productivity: recent trends, challenges and future perspectives. – *Forestry*, 87, 109–128.
- DeLucia, E.H., Drake, J.E., Thomas, R.B., Gonzalez-Meler, M. 2007. Forest carbon use efficiency: Is respiration a constant fraction of gross primary production? – *Global Change Biology*, 13, 1157–1167.
- D'Odorico, P., Gonsamo, A., Pinty, B., Gobron, N., Coops, N., Mendez, E., Schaepman, M.E. 2014. Intercomparison of fraction of absorbed photosynthetically active radiation products derived from satellite data over Europe. – *Remote Sensing of Environment*, 142, 141–154.
- Eenmäe, A., Nilson, T., Lang, M. 2011. A note on meteorological variables related trends in the MODIS NPP product for Estonia. – *Forestry Studies / Metsanduslikud Uurimused*, 55, 60–63.
- FAO, IIASA, ISRIC, ISS-CAS, JRC. 2012. Harmonized World Soil Database (version 1.2). FAO, Rome, Italy and IIASA, Laxenburg, Austria.
- Finér, L., Ohashi, M., Noguchi, K., Hirano, Y. 2011. Fine root production and turnover in forest ecosystems in relation to stand and environmental characteristics. – *Forest Ecology and Management*, 262, 2008–2023.
- GFOI. 2013. Integrating remote-sensing and ground-based observations for estimation of emissions and removals of greenhouse gases in forests: Methods and Guidance from the Global Forest Observations Initiative: Pub: Group on Earth Observations, Geneva, Switzerland, 2014. ISBN 978-92-990047-4-6.
- Härkönen, S., Lehtonen, A., Eerikäinen, K., Peltoniemi, M., Mäkelä, A. 2011. Estimating forest carbon fluxes for large regions based on process-based modelling, NFI data and Landsat satellite images. – *Forest Ecology and Management*, 262, 2364–2377.
- Härkönen, S., Pulkkinen, M., Duursma, R., Mäkelä, A. 2010. Estimating annual GPP, NPP and stem growth in Finland using summary models. – *Forest Ecology and Management*, 259, 524–533.
- Härkönen, S., Tokola, T., Packalén, P., Korhonen, L., Mäkelä, A. 2013. Predicting forest growth based on airborne light detection and ranging data, climate data, and a simplified process-based model. – *Canadian Journal of Forest Research*, 43, 364–375.

- IDB. 2016. State register for accounting of forest resource. (Metsaressursi arvestuse riikliku registri põhimäärus). – Riigi Teataja, RT I, 12.01.2016, 2. (In Estonian).
- IPCC. 2006. 2006 IPCC Guidelines for National Greenhouse Gas Inventories. – Eggleston, S., Buendia, L., Miwa, K., Ngara, T., Tanabe, K (eds.). Hayama: Institute of Global Environmental Strategies (IGES). Volume 4: Agriculture, Forestry and Other Land Use.
- IUSS Working Group WRB. 2014. World Reference Base for Soil Resources 2014. International soil classification system for naming soils and creating legends for soil maps. World Soil Resources Reports No. 106. FAO, Rome.
- Kandare, K., Ørka, H.O., Dalponte, M., Næsset, E., Gobakken, T. 2017. Individual tree crown approach for predicting site index in boreal forests using airborne laser scanning and hyperspectral data. – *International Journal of Applied Earth Observation and Geo-information*, 60, 72–82.
- Kiviste, A., Hordo, M., Kangur, A., Kardakov, A., Laarmann, D., Lilleleht, A., Metslaid, S., Sims, A., Korjus, H. 2015. Monitoring and modeling of forest ecosystems: the Estonian Network of Forest Research Plots. – *Forestry Studies / Metsanduslikud Uurimused*, 62, 26–38.
- Kliimaatlas. 1970. Climate data in Estonia (Eesti NSV kliimaatlas). Eesti NSV Hüdrometeoroloogia teenistuse valitsus. Tallinn.
- Kölli, R. 1988. Phytoproductivity of Estonian soils in forest land. – *Почвоведение*, 4, 96–107. (In Russian).
- Kölli, R., Asi, E., Köster, T. 2004. Organic carbon pools in Estonian forest soils. – *Baltic Forestry*, 10(1), 19–26.
- Kölli, R., Ellermäe, O., Köster, T., Lemetti, I., Asi, E., Kauer, K. 2009. Stocks of organic carbon in Estonian soils. – *Estonian Journal of Earth Sciences*, 58, 95–108.
- Kölli, R., Kanal, A. 2010. The management and protection of soil cover: an ecosystem approach. – *Forestry Studies / Metsanduslikud Uurimused*, 53, 25–34.
- Kuusk, A., Kuusk, J., Lang, M. 2016. Albedo of the forested landscape at the SMEAR-Estonia research station. – *Baltic Forestry*, 22(2), 390–395.
- Lang, M., Traškovs, A., Gulbe, L. 2013. Assessment of NTSG MODIS NPP product for forests in Kurzeme region, Latvia. – *Forestry Studies / Metsanduslikud Uurimused*, 58, 26–36.
- Liu, C., Westman, C.J., Berg, B., Kutsch, W., Wang, G.Z., Man, R., Ilvesniemi, H. 2004. Variation in litterfall-climate relationships between coniferous and broadleaf forests in Eurasia. – *Global Ecology and Biogeography*, 13, 105–114.
- Liu, J., Chen, J.M., Cihlar, J., Park, W.M. 1997. A process-based boreal ecosystem productivity simulator using remote sensing inputs. – *Remote Sensing of Environment*, 62, 158–175.
- Mäkelä, A., Valentine, H.T. 2001. The ratio of NPP to GPP: evidence of change over the course of stand development. – *Tree Physiology*, 21, 1015–1030.
- Makkonen, K., Helmisaari, H.S. 2001. Fine root biomass and production in Scots pine stands in relation to stand age. – *Tree Physiology*, 21, 193–198.
- Metsakorralduse. 2017. Forest inventory act. (Metsa korraldamise juhend). – RT I, 22.02.2017, 11. (In Estonian).
- Moreno, A., Hasenauer, H. 2016. Spatial downscaling of European climate data. – *International Journal of Climatology*, 36, 1444–1458.
- Moreno, M., Neumann, M., Hasenauer, H. 2016. Optimal resolution for linking remotely sensed and forest inventory data in Europe. – *Remote Sensing of Environment*, 183, 109–119.
- Mullakaardi. 2001. The fine-scale map of Estonian soils. (Vabariigi digitaalse suuremõõtkavalise mullastiku kaardi seletuskiri). Maa-amet, Tallinn. [WWW document]. – <http://geoportaal.maaamet.ee/est/Andmed-ja-kaardid/Mullastiku-kaart-p33.html> [Accessed 16 April 2016]. (In Estonian).
- Neumann, M., Moreno, A., Thurnher, C., Mues, V., Härkönen, S., Mura, M., Bouriaud, O., Lang, M., Cardellini, G., Thivolle-Cazat, A., Bronisz, K., Merganic, J., Alberdi, I., Astrup, R., Mohren, F., Zhao, M., Hasenauer, H. 2016. Creating a regional MODIS satellite-driven net primary production dataset for European forests. – *Remote Sensing*, 8(7), 554, doi:10.3390/rs8070554.
- Neumann, M., Mues, V., Moreno, A., Hasenauer, H., Seidl, R. 2017. Climate variability drives recent tree mortality in Europe. *Global Change Biology*, 00, 1–10, <https://doi.org/10.1111/gcb.13724> (In press).
- Nilson, T., Rennel, M., Luhamaa, A., Hordo, M., Olesk, A., Lang, M. 2012. MERIS GPP/NPP product for Estonia: I. Algorithm and preliminary results of simulation. – *Forestry Studies / Metsanduslikud Uurimused*, 56, 56–78.
- Noe, S.M., Niinemets, Ü., Krasnova, A., Krasnov, D., Motallebi, A., Kängsepp, V., Jõgiste, K., Hörrak, U., Komsaare, K., Mirmo, S., Vana, M., Tammet, H., Bäck, J., Vesala, T., Kulmala, M., Petäjä, T., Kangur, A. 2015. SMEAR Estonia: Perspectives of a large-scale forest ecosystem – atmosphere research infrastructure. – *Forestry Studies / Metsanduslikud Uurimused*, 63, 56–84.

- Olofsson, P., Eklundh, L., Lagergren, F., Jonsson, P., Lindroth, A. 2007. Estimating net primary production for Scandinavian forests using data from Terra/MODIS. – *Advances in Space Research*, 39, 125–130.
- Olson, R.J., Johnson, K.R., Zheng, D.L., Scurlock, J.M.O. 2001. Global and regional ecosystem modeling: Databases of model drivers and validation measurements. Oakridge Laboratory: Oak Ridge, TN, USA.
- Ostonen, I., Lohmus, K., Pajuste, K. 2005. Fine root biomass, production and its proportion of NPP in a fertile middle-aged Norway spruce forest: Comparison of soil core and ingrowth core methods. – *Forest Ecology and Management*, 212, 264–277.
- Quaife, T., Quegan, S., Disney, M., Lewis, P., Lomas, M., Woodward F.I. 2008. Impact of land cover uncertainties on estimates of biospheric carbon fluxes. – *Global Biogeochemical Cycles*, 22, 1–12.
- Raich, J.W., Nadelhoffer, K.J. 1989. Belowground carbon allocation in forest ecosystems: global trends. – *Ecology*, 70, 1346–1354.
- Raudsaar, M., Pärt, E., Adermann, V. 2016. Forest resources. In: *Yearbook Forest 2014*. Tallinn, Keskkonnaagentuur. 1–61.
- Schubert, P., Lagergren, F., Aurela, M., Christensen, T., Grelle, A., Heliasz, M., Klemetsson, L., Lindroth, A., Pilegaard, K., Vesala, T., Eklundh, L. 2012. Modeling GPP in the Nordic forest landscape with MODIS time series data – comparison with the MODIS GPP product. – *Remote Sensing of Environment*, 126, 136–147.
- Sims, A., Mändma, R., Laarmann, D., Korjus, H. 2014. Assessment of tree mortality on the Estonian Network of Forest Research Plots. – *Forestry Studies / Metsanduslikud Uurimused*, 60, 57–68.
- Stagakis, S., Markos, N., Vanikiotis, T., Tzotsos, A., Sykioti, O., Kyriassis, A. 2015. sCASE: A primary productivity monitoring system for the forests of North Pindus National Park (Epirus, Greece). – *European Journal of Remote Sensing*, 48, 223–243.
- Tan, B., Woodcock, C.E., Hu, J., Zhang, P., Ozdogan, M., Huang, D., Yang, W., Knyazikhin, Y., Myrneni, R.B. 2006. The impact of gridding artifacts on the local spatial properties of MODIS data: Implications for validation, compositing, and band-to-band registration across resolutions. – *Remote Sensing of Environment*, 105, 98–114.
- Tang, J., Luyssaert, S., Richardson, A.D., Kutsch, W., Janssens, I.A. 2014. Steeper declines in forest photosynthesis than respiration explain age-driven decreases in forest growth. – *Proceedings of the National Academy of Sciences*, 111, 8856–8860.
- Tomppo, E., Gschwantner, T., Lawrence, M., McRoberts, R. 2010. *National Forest Inventories: Pathways for common reporting*. Springer: Berlin, Germany.
- Tooming, H. 1977. Solar radiation and yield formation. Gidrometeoizdat, Leningrad, Russia.
- Turner, D.P., Ritts, W.D., Cohen, W.B., Gower, S.T., Running, S.W., Zhao, M., Costa, M.H., Kirschbaum, A.A., Ham, J.M., Saleska, S.R., Ahl, D.E. 2006. Evaluation of MODIS NPP and GPP products across multiple biomes. – *Remote Sensing of Environment*, 102, 282–292.
- Vanninen, P., Mäkelä, A. 1999. Fine root biomass of Scots pine stands differing in age and soil fertility in southern Finland. – *Tree Physiology*, 19, 823–830.
- Varik, M., Aosaar, J., Uri, V. 2009. Biomass production in silver birch stands in *Oxalis* site type. – *Forestry Studies / Metsanduslikud Uurimused*, 51, 5–16.
- Waring, R.H., Milner K.S., Jolly, W.M., Phillips, L., McWethy, D. 2006. Assessment of site index and forest growth capacity across the Pacific and Inland Northwest U.S.A. with a MODIS satellite-derived vegetation index. – *Forest Ecology and Management*, 228, 285–291.
- Xin, Q., Olofsson, P., Zhu, Z., Tan, B., Woodcock, C.E. 2013. Toward near real-time monitoring of forest disturbance by fusion of MODIS and Landsat data. – *Remote Sensing of Environment*, 135, 234–247.
- Yuan, Z.Y., Chen, H.Y.H. 2012a. Indirect methods produce higher estimates of fine root production and turnover rates than direct methods. – *PLoS ONE* 7(11): e48989. doi:10.1371/journal.pone.0048989.
- Yuan, Z.Y., Chen, H.Y.H. 2012b. A global analysis of fine root production as affected by soil nitrogen and phosphorus. – *Proceedings of the Royal Society B: Biological Sciences*, 279, 3796–3802.
- Zhao, M., Heinsch, F.A., Nemani, R.R., Running, S.W. 2005. Improvements of the MODIS terrestrial gross and net primary production global data set. – *Remote Sensing of Environment*, 95, 164–176.
- Zhao, M., Running S.W., Heinsch F.A., Nemani R.R. 2011. MODIS-derived terrestrial primary production. – Ramachandran, B., Justice, C.O., Abrams, M.J. (eds.). *Land Remote Sensing and Global Environmental Change: NASA's Earth Observing System and the Science of ASTER and MODIS*. New York, Springer-Verlag. 635–660.

Kiirguse kasutamise efektiivsuse põhimõttele tuginevate taimkatte neto-produktsiooni hinnangute analüüs muldkatte fütoproduktiivsuse mudeli abil

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Kokkuvõte

Taimkatte neto-produktsiooni (NPP) pidev seire on oluline nii elukeskkonda mõjutavate tegurite kui ka muldkatte produktiivsuse jälgimiseks. Metsade fütoproduktsiooni saab hinnata statistilise valimhinnanguga kogutud andmeid kasutades (statistiline metsainventuur) (Tomppo *et al.*, 2010; GFOI, 2013; Bontemps & Bouriard, 2014) või teisalt satelliitkaugseire abil mõõdetud fotosünteesiliselt aktiivse kiirguse suhtelise neeldunud osa (fAPAR), valguse kasutamise tõhususe (LUE) ja fotosünteesi piiravate tegurite (veeauru defitsiit ja õhutemperatuur) kaudu (Zhao *et al.*, 2005). Uuringu eesmärgiks oli kasutada Eesti mullakaardi infot satelliitseirele tuginevate NPP hinnangute analüüsimiseks. Töös kasutati 2914 vaatlusala, mis vastasid ristkoordinaatide süsteemis 500×1000 m suurustele MODIS NPP produkti pikslitele (joonis 1) ja olid 1) üle 30 km Läänemere rannikust sisemaa suunas, 2) kaetud vähemalt 75% ulatuses metsaeraldise andmetega, 3) alla 10% pindalast mõjutatud tugevatest häiringutest alates 2001. aastast, ja 4) metsandike piiridest 1 km seespool.

Mullakaardi andmebaasi igale mullakontuurile arvutati Kõlli (1988) töös joonisel 3.2 esitatud mudeli abil taimkatte maa-pealse osa potentsiaalse fütoproduktiivsuse (SPP) hinnang. Gleimuldadel kasutati turba түsedusest sõltuvat korrektsiooni (1) ja lisaks rakendati peenliiva ja liiva lõimise-ga leetjatel gleimuldadel faktorit 0,85. Taimkatte maa-aluse osa NPP hinnang lisati faktori 1,2 abil, mis vastab keskmiselt parasvöötme keskealistele ja vanematele metsadele IPCC (2006) järgi ja saadi mulla viljakusele tuginev NPP_{SPP} . Metsaregistri

andmetest võetud puidu juurdekasvul põhineva NPP hinnangu (NPP_{FIDB}) arvutamiseks kasutati biomassi laiendustegurit $BCEFi = 0,72$ (IPCC 2006) ja lisati ka varise hinnangud (2, 3). Peenjuurte juurdekasvu hinnang võeti võrdseks varise toodanguga. Mullakaardi ja metsaregistri andmetele tuginevad NPP hinnangud olid omavahel loogilises kooskõlas (joonised 2 ja 3).

Andmestike (tabel 1) analüüsiks kasutati regressioonmudelit (4), mille argumentideks olid Eenmäe *et al.* (2011) kirjeldatud Eesti territoriaalsed tsoonid (Z_{DAO}) (teki-vad globaalsetes NPP hinnangutes väikese ruumilahutusega ilmastikuandmete tõttu), NPP_{SPP} ja metsaregistri andmetest arvutatud okasmetsa osakaal K (%). Mudeli (4) parameetrite hinnangutest (tabel 2) selgus, et NPP_{FIDB} suureneb Eestis läänest itta nagu NPP_{SPP} ja kahaneb koos okaspuistute osakaalu kasvuga, sest Eestis domineerivad väheviljakatel muldadel enamasti männikud (madalsoodes siiski ka lehtpuupuis-tud). Kõikide LUE-tüüpi mudelite puhul ilmnes selgelt hinnangute oluliselt kitsam haare IQR (tabel 2) võrreldes mulla potentsiaalse fütoproduktiivsusega. Globaalsetele ilmaandmetele tuginevate NPP_{NTSG} ja NPP_{NTSG_GPP} seos NPP_{SPP} väärtustega oli äraspidine ja tähtsaimaks teguriks osutus hoopis Z_{DAO} . Ruumiliselt parema lahutusega ilmaandmete kasutamise tulemuse-na Neumann *et al.* (2016) saadud NPP_{EURO} kasvas läänest ida suunas nagu ka NPP_{SPP} . NPP_{EURO} puhul oli NPP aga saadud lehe-pinnaindeksiga seotud kasvu- ning säilitushingamise arvestamise kaudu fotosünteesi üldisest produktist (GPP). Arvatavas-ti nende lisaparametrite vigade tõttu jäi

NPP_{EURO} ja NPP_{SPP} seos siiski negatiivseks. Kõige sisukama kooskõla mulla fütoproductiivsusega andsid Eesti andmetel põhinevale maakattekaardile ja kõrge ruumilise lahutusega ilmaandmetele tuginev Nilson *et al.* (2012) töös avaldatud NPP hinnangud (tabel 1), mille sisendiks kasutatud fAPAR-i ja NPP_{SPP} vahel oli samuti positiivne korrelatsioon (joonis 4, tabel 2).

Kokkuvõtteks järeldati, et rutiinselt toodetavate üleilmsete NPP hinnangute vigade vähendamiseks tuleks võtta kasutusele lokaalselt parandatud maakattekaardid ja suurendada fAPAR-i mõõtmistäpsust. Eesti mullakaart ja metsade takseerkirjedused osutusid unikaalseteks referentsandmestikeks satelliitseirele tuginevate NPP hinnangute headuse analüüsimisel.

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