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MERIS GPP/NPP product for Estonia: I. Algorithm and preliminary results of simulation

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Abstract. A light use efficiency (LUE) type model named EST_PP to simulate the yearly gross primary production (GPP) and net primary production (NPP) of Estonian land on a 1 km^2 grid is described. The model is based on MERIS (MEdium Resolution Imaging Spectrometer) satellite images to describe the fraction of photosynthetically active radiation (fAPAR) and leaf area index (LAI) as well as meteorological reanalysis datasets on 11 km^2 grid produced by Estonian Meteorological Institute (EMHI) and Tartu University (TU) by means of the HIRLAM (High Resolution Limited Area Model) numerical weather prediction model. The land cover map of Estonia needed for the model was derived using DMCii (Disaster Monitoring Constellation International Imaging) SLIM-6-22 (Surrey Linear Imager – 6 channel – 22 m resolution) images and ancillary information. The EST_PP model was run for the period from years 2003 to 2011. The results of GPP and NPP simulation are compared with the available global MODIS (Moderate Resolution Imaging Spectroradiometer) GPP/NPP product and with the Estonian statistical data on yearly volume increment in forests and on yield of agricultural crops. The NPP simulation results on coniferous and deciduous forests are compared with the data from tree ring analyses from different counties. These comparisons show us that the simulated country average yearly NPP values for Estonian forests agree reasonably well with the indirect estimates from other sources, taking into account the rather high uncertainty of the model predictions, uncertainty of forest inventory-based estimates and limited representativity of existing tree ring data. However, problems arise with the ability of present versions of EST_PP and MODIS NPP models to adequately simulate the regional differences of productivity and of variability of productivity in different years. The model needs some modification and the basic LUE principles to be tested in Estonia. Nevertheless, the MODIS NPP and EST_PP models offer additional possibilities to map yearly productivity and carbon sequestration by Estonian vegetation. There is a perspective to add the model-simulated NPP values into the national inventory datasets.

Key words: forest productivity, primary production, carbon balance, remote sensing, satellite images, MERIS.

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Introduction

Global and regional carbon balance data are needed to understand modern global warming trends. As vegetation plays an important role in the carbon balance, its constant change and the change dynamics should be closely monitored. Now, since the second commitment period of the Kyoto protocol (United Nations, 2012) of CO_2 emission reduction has been approved, countries have to continue reporting about their carbon emissions and balance components. The direct monitoring of CO_2 concentration in the atmosphere over a country by satellite remote sensing is still problematic. Typically, CO_2 fluxes and yearly budget in the atmospheric boundary layer are measured by means of eddy covariance techniques (Baldocchi *et al*., 1988) from gradient towers. In Estonia, the methodology of ground-based measurements of CO_2 via in situ measurements is at its early development stage and so far no systematic results of measurements are available. It is practically impossible to cover the whole Estonia in a statistically meaningful way by the gradient towers. Due to these problems the CO_2 budget for official reports is typically estimated by budget components and using default emission factors for different land cover classes. Alternative option for the use of default emission factors to estimate the contribution of vegetation in the CO_2 balance could be application of the respective simulation models. There exist tens of different models to calculate vegetation growth and productivity, gross primary production (GPP), net primary production (NPP) or net ecosystem exchange (NEE) on global or regional levels (Potter *et al*., 1993, Heinsch *et al*., 2003, Schwalm *et al*., 2010, Zhao *et al*., 2011, among many others). According to their general principle, these models can be divided into at least three categories:

- Process-based models in which the quantitative models of photosynthesis, respiration and growth are applied;
- Light use efficiency (LUE) concept based models which rely on the linear relation between the absorbed photosynthetically active radiation (PAR) and NPP or GPP. The LUE concept was first suggested by Monteith (1972, 1977);
- Various empirical and semi-empirical growth models and statistical models capable to extend the measured NPP or NEE values from CO_2 flux tower measurements onto a larger territory.

There is an important aspect related to the vegetation NPP models concerning the yearly inventory of forest growth, yield of agricultural fields and carbon sequestration by vegetation. The models can rely very much on satellite images as inputs and thus can provide operative and objective overview of vegetation state and phenology. This kind of information is not practically accessible via traditional inventory methods on large territories, such as country and even regional levels. Moreover, NPP models are effective tools to understand how the vegetation growth and productivity are influenced by several environmental factors, e.g. meteorological factors. For the inputs, the NPP models need information about the key meteorological factors (temperature, cloudiness, moisture) of the whole territory under consideration. Typically, the set of meteorological stations is not sufficient to provide adequate spatial representation of the key meteorological data. There have been attempts to estimate the needed meteorological factors from satellite images, however, the majority of NPP models rely on inputs from the so-called reanalysis datasets of meteorological variables produced by numerical weather prediction models and from existing observations. MODIS GPP/NPP model uses the NCEP/DOE II (National Centers for Environmental Prediction) global meteorological reanalysis dataset which has a rather coarse resolution ($1^o \times 1.25^o$, i.e. of the order of magnitude of 100 km). Recently, for the Baltic Sea region a high-resolution reanalysis (11×11 km^2) database BaltAn65+

PAR

was created (Luhamaa *et al.*, 2011), which is much more suitable for NPP models that typically run at 1 km^2 resolution.

Below, a LUE type GPP/NPP model named EST_PP is described and applied to calculate GPP and NPP of Estonian land surface, where the main attention is paid to the forests. The results of model simulation are compared with the existing MODIS GPP/NPP product over Estonia, with the data from Estonian national statistics and the results of tree-ring width analysis.

The current version of the EST_PP model relies on MERIS images and BaltAN65+ high-resolution reanalysis database. The basic ideas of the model are essentially the same as used in the MODIS GPP/NPP product (Heinsch *et al.*, 2003), however, some modifications have been introduced into the EST_PP model. The MODIS algorithm was chosen because the NASA MODIS science team provides global 8-day GPP and yearly GPP/NPP estimates at 1 km^2 scale from year 2000 onwards. Thus, there is a possibility to compare the results of our model simulation with an already existing data set. There have been several attempts to test the MODIS NPP algorithm at local or regional levels (e.g. Kim *et al.*, 2007; Olofsson *et al.*, 2007; Huang *et al.*, 2010). Typically, conclusions were drawn that the LUE concept seems to work, however, local meteorological data and higher resolution satellite images should be preferred as inputs to the model and some of the model constants should be revised.

Material and Methods

Description of the EST_PP model

For GPP/NPP calculations, Estonia was covered with a fixed 1 × 1 km^2 grid in ETRS89-LAEA (Lambert azimuthal equal-area) projection system coordinates and all necessary data were resampled into that grid. Following the principles of LUE models, the daily GPP for a 1 × 1 km^2 vegetated pixel was calculated as:

$$GPP = PAR\, fAPAR\, \varepsilon\, g(T)\, h(W), \tag{1}$$

where PAR (MJ m^{-2} day^{-1}) is the daily incident photosynthetically active radiation (PAR, 0.4–0.7 µm), $fAPAR$ is the fraction of absorbed PAR; and ε (gC MJ^{-1}) is the maximum achievable light use efficiency adjusted by reduction functions that account for limiting effects of air temperature $g(T)$ and water $h(W)$ stresses. To obtain yearly GPP, Eq. 1 is summed over all days of the year.

Incident daily PAR was calculated as 0.45 of the total integral radiation:

$$PAR = 0.45Q \tag{2}$$

In our model, the daily sums of the measured integral radiation Q from Tartu-Tõravere meteorological station of the Estonian Meteorological and Hydrological Institute were used, the station belonging to the global Baseline Surface Radiation Network (BSRN). The daily measured Q values in Tõravere were extrapolated to all pixels in Estonia by using the daily total cloudiness estimate for the pixel as obtained from the BaltAN65+ regional reanalysis database for the Baltic Sea region (Luhamaa *et al.*, 2011). To calculate the daily total value of Q at any pixel location in Estonia (given by its day of the year (DOY) number), the following relation was used:

$$Q_{pixel}(DOY) = Q_{meas,T}(DOY)\,\frac{CCF\left(CC_{pixel}(DOY)\right)}{CCF\left(CC_{T}(DOY)\right)} \tag{3}$$

Here $Q_{meas,\,T}$ is the daily measured total radiation at Tõravere for the day of interest and CCF is the cloud cover factor for what an empirical second order polynomial approximation was used:

$$CCF = -0.006788CC^2 + 0.010986CC + \\ + 0.953658, R^2 = 0.683\ , \tag{4}$$

where CC is the daily average of the total cloudiness. The regression was derived from the Tõravere data records for the period of year from DOY = 100 up to DOY = 290, i.e. for the period predominantly free of snow cover. The total cloudiness estimates, as determined visually at the meteorological station in Tõravere (CC_T) or extracted from the BaltAN65+ regional meteorological reanalysis data set for any 11 × 11 km pixel in (CC_{pixel}) Estonia, were used.

In the EST_PP model, fAPAR and LAI estimates produced by the TOA-VEG processor of the MERIS Vegetation Processor 2.0.6 of BEAM 4.0 were applied. This procedure derives the estimates of fAPAR and LAI from MERIS top-of-atmosphere reflectance (level 2) data (Gobron *et al*., 2004, Baret *et al*., 2006).

For the temperature reduction factor $g(T)$, the equation developed for the Terrestrial Ecosystem Model (TEM) (Raich *et al*., 1991) was used:

$$g(T) = \frac{(T - T_{min})(T - T_{max})}{(T - T_{min})(T - T_{max}) - \left(T - T_{opt}\right)^2}$$

$$g(T) = 0, if\ T < T_{min} \text{ or } T > T_{max} \tag{5}$$

T being the daily average air temperature (°C), and T_{min}, T_{opt}, and T_{max} – the minimum, optimal, and maximum temperatures (°C) for photosynthetic activity, respectively. The values of T_{min} = 2 °C, T_{opt} = 26 °C, and T_{max} = 39 °C (Raich *et al*., 1991) were used for all land cover types in this modelling experiment. These values are used in Fig. 1, to present the shape of the temperature reduction function.

A parallel version of the EST_PP model was also run to study the effect of the temperature reduction factor on final estimates of GPP and NPP. In the parallel version, the temperature reduction function $f(T)$ from the MODIS GPP/NPP algorithm (Heinsch *et al*., 2003) was used. $f(T)$ is defined according to the daily minimum air temperature T_{min} as follows:

$$f(T) = 0, \text{if } T_{min} < TMIN_{min}$$

$$f(T) = \frac{T - TMIN_{min}}{TMIN_{max} - TMIN_{min}}, \quad \text{if } TMIN_{min} < T_{min} < TMIN_{max} \tag{5a}$$

$$f(T) = 1, \text{if } T_{min} > TMIN_{max}$$

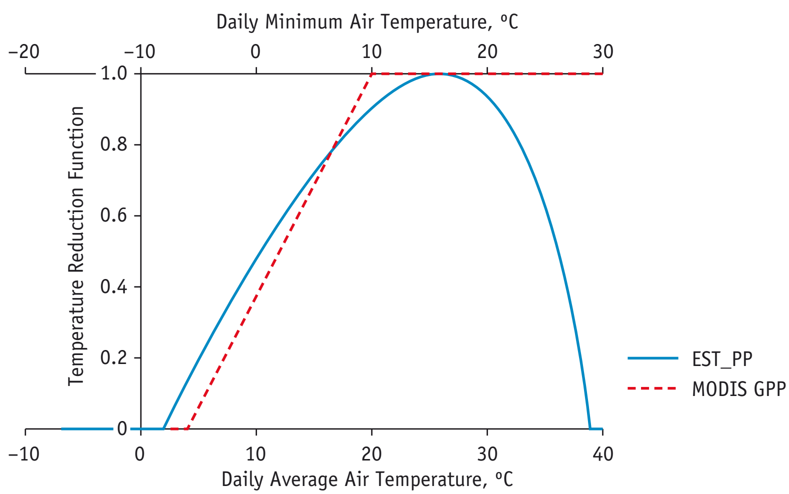

Figure 1. An example of the shape of temperature reduction factors used in the EST_PP and MODIS GPP algorithms. The EST_PP algorithm uses the daily (day and night) average air temperature (lower x-axis) while the MODIS algorithm uses the daily minimum air temperature (upper x-axis). The upper and lower x-axes are shifted by 10 °C in the example.

Joonis 1. Näide temperatuuri mõjuteguritest, mida kasutati EST_PP ja MODIS GPP algoritmides. EST_PP algoritm kasutab ööpäevast keskmist õhutemperatuuri (alumine x-telg), MODIS algoritm aga ööpäeva miinimumtemperatuuri (ülemine x-telg). Ülemine ja alumine x-telg on nihutatud 10 °C võrra.

In the model, the air temperature through the temperature reduction factor determines the beginning and end of the vegetation period. The shapes of the two temperature reduction functions are compared in Fig. 1. For the MODIS algorithm, values of $TMIN_{min}$ = –6 °C and $TMIN_{max}$ =9.94 °C (corresponding to the values for deciduous forest in Table 1) are used in this example.

For the water stress reduction function $h(W)$ the function from MODIS GPP/NPP algorithm (Heinsch *et al.*, 2003) was used, defined by the daily water vapour pressure deficit in the air:

$$h(W) = 1, \text{if } VPD < VPD_{min}$$
$$h(W) = 1 - \frac{VPD - VPD_{min}}{VPD_{max} - VPD_{min}}, \quad \text{if } VPD_{min} < VPD < VPD_{max} \qquad (6)$$
$$h(W) = 0, \text{if } VPD > VPD_{max}$$

Here VPD_{min} and VPD_{max} are biome-specific values given in the look-up table (see Table 1). An example of the shapes of function h(W) that were used for the three types of forest are presented in Fig. 2.

The daytime water vapour pressure deficit (VPD) was calculated from the average relative air humidity W (%) and temperature T (°C) at 2 m height at 06, 12 and 18 hours UTC. The saturation water vapour pressure SVP (hPa) was calculated from the air temperature using the equation by Buck (1981):

$$SVP = 6.1121\exp\left[\left(18.678 - \frac{T}{234.5}\right)(T/(257.14 + T))\right] \qquad (7)$$

and the water vapour pressure deficit as:

$$VPD = (1 - W/100)SVP\,. \qquad (8)$$

The calculation of NPP, considering all the necessary respiration terms was done according to the latest version of MODIS NPP model (Zhao & Running, 2011).

To calculate respiration, an estimate of the leaf area index (LAI, m^2/m^2) from MERIS images was used. For the maintenance respiration, first the leaf mass was calculated from LAI using the specific leaf area (SLA, m^2/kgC), whose value is given in the lookup table (Table 1) for each biome:

$$Leaf\_Mass = LAI/SLA\,. \qquad (9)$$

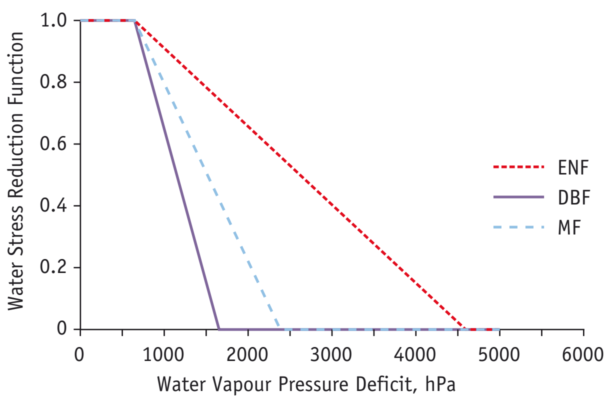

Figure 2. The used reduction function due to water stress as a function of daytime average water vapour pressure deficit for forests: ENF – evergreen needleleaf forest, DBF – deciduous broadleaf forest, MF – mixed forest. It is assumed that there is no water stress, if *VPD* < 650 hPa.

Joonis 2. Mudelarvutustes kasutatud veestressi mõjutegurid metsadele funktsioonina päevakeskmisest veeaururõhu defitsiidist: ENF – igihaljad okasmetsad, DBF – heitlehelised lehtmetsad, MF – segametsad. Eeldatakse, et veestressi ei ole kui VPD < 650 hPa.

Then, the leaf maintenance respiration (*Leaf_MR*) is calculated as:

$$Leaf_{MR} = Leaf\_Mass * Leaf\_MR\_base * \\ * Q10\_mr\_leaf^{(Tavg-20)/10} \quad , (10)$$

where the values of *Leaf_MR_base* and *Q10_mr* are given in the lookup table (Table 1) for each biome and *Tavg* (°C) is the average daily air temperature. *Q10_mr* for leaves is assumed to be a function of the temperature:

$$Q10\_mr\_leaf = 3.22 - 0.0466 * Tavg \quad (11)$$

The mass of fine roots (*Fine_Root_Mass*) was calculated as proportional to the leaf mass, with the biome-specific proportionality coefficient *froot_leaf_ratio:*

$$Fine\_Root\_Mass = Leaf\_Mass * \\ * froot\_leaf\_ratio \quad (12)$$

The maintenance respiration for the fine roots was calculated as:

$$Froot\_MR = Fine\_Root\_Mass * \\ froot\_mr\_base * Q10\_mr^{(\mathrm{Tavg}-20)/10} \quad (13)$$

where *froot_mr_base* is another biome-specific coefficient given in the lookup table (Table 1).

Daily net photosynthesis for each pixel was obtained as:

$$PSNet = GPP - Leaf\_MR - Froot\_MR \quad (14)$$

Yearly NPP for each pixel is obtained as the yearly sum of daily *PSNet* minus livewood maintenance respiration minus growth respiration. Similarly to Zhao & Running (2010), the growth respiration is assumed to be 25% of NPP:

$$NPP\_year = 0.8[\sum_{DOY=1}^{365}((PSNet) \\ -Livewood\_MR)] \quad (15)$$

$$Livewood\_mass = annual\_leaf\_mass\_max * \\ *livewood\_leaf\_ratio \quad (16)$$

$$Livewood\_MR = Livewood\_mass * \quad (17) \\ *livewood\_mr\_base * Q10\_mr^{(\mathrm{Tavg}-20)/10} \quad ,$$

where *livewood_mr_base* and *livewood_leaf_ratio* are coefficients given in the lookup table (Table 1).

Table 1. Lookup table for biome properties from (Zhao & Running, 2010a). Landcover types used in EST_PP: Evergreen Needleleaf Forest (ENF), Deciduous Broadleaf Forest (DBF), Mixed Forest (MF), Open Shrublands (OSH), Grassland (GRA) and Cropland (CRO). Some of the landcover classes used in (Zhao & Running, 2010a) are excluded in EST_PP (such as Evergreen Broadleaf Forest (EBF), Deciduous Needleleaf Forest (DNF)).

Tabel 1. Bioomi-parameetrite otsingutabel (Zhao & Running, 2010a). EST_PP mudelis kasutatud maakatteklassid: Igihaljas okasmets (ENF), heitleheline laialeheline mets (DBF), segamets (MF), avatud põõsastik (OSH), rohumaa (GRA) ja põllumaa (CRO). Mõned maakatteklassid, mis kasutusel (Zhao & Running, 2010a) on välja jäetud EST_PP mudelis (nt igihaljas laialeheline mets (EBF), heitleheline okasmets (DNF)).

UMD_VEG_LC quantity, unit	ENF	DBF	MF	OSH	GRA	CRO
LUEmax, kgC/MJ	0.000962	0.001165	0.001051	0.000841	0.000860	0.001044
TMINmin, °C	-8.00	-6.00	-7.00	-8.00	-8.00	-8.00
TMINmax, °C	8.31	9.94	9.50	8.80	12.02	12.02
VPDmin, Pa	650	650	650	650	650	650
VPDmax, Pa	4600	1650	2400	4800	5300	4300
SLA, m^2/kgC	14.1	21.8	21.5	11.5	37.5	30.4
Q10*	2.0	2.0	2.0	2.0	2.0	2.0
Froot_leaf_ratio	1.2	1.1	1.1	1.3	2.6	2.0
Livewood_leaf_ratio	0.182	0.203	0.203	0.040	0	0
Leaf_mr_base	0.00604	0.00778	0.00778	0.00519	0.0098	0.0098
Froot_mr_base	0.00519	0.00519	0.00519	0.00519	0.00819	0.00819
Livewood_mr_base	0.00397	0.00371	0.00371	0.00218	0	0

*For leaves Q10_mr is given by Eq. 11

To calculate all the respiration components, several coefficients (*froot_leaf_ratio* (kgC/kgC), *Leaf_MR_base* (kgC/kgC/day, 20C), *froot_mr_base* (kgC/kgC/day, 20C), *livewood_leaf_ratio* (kgC/kgC), *livewood_mr_base* (kgC/kgC/day, 20C), *Q10_mr*) are supposed to be given in the annual part of the biome-specific input lookup table that was adapted from Zhao & Running (2010, 2010a). In the EST_PP model, the values from Table 1 were used except for the temperature reduction factor.

EST_PP model inputs

The following inputs were used to run the EST_PP model:

- Estonian land cover map at 1 km^2 resolution. The grid was fixed and all the meteorological data as well as fAPAR and LAI data were resampled into that grid. The following land cover classes were distinguished using two DMCii images from summer 2011 and multi-source ancillary data: Deciduous Broadleaf Forest, Mixed Forest, Evergreen Needleleaf Forest, Cropland, Grasslands, Open Shrublands, Marshes/Fens, Bog, Peat Extraction Areas, Settlements and Other Land. In the GPP/NPP model calculations, wetlands and settlements were excluded from the analysis. The same land cover map was used for the whole period of the simulation from 2003 to 2011;
- A lookup table containing the necessary input parameter values (ε, T_{min}, T_{opt}, T_{max}, SLA, leaf_MR_base, froot_leaf_ratio, froot_MR_base, Q10mr, livewood_MR_base, livewood_leaf_ratio) for all land cover classes included in the land cover map. Similarly to Raich *et al*. (1991) the values of T_{min} = 2 °C, T_{opt} = 26 °C and T_{max} = 39 °C were used, while the rest set of parameters in the lookup table were used as in Zhao *et al*. (2011);
- Daily sums of integral global radiation and total cloudiness measured at Tõravere (EMHI);
- Daily values of MERIS *fAPAR* and green leaf area index (LAI) as produced by the ESA BEAM software and resampled into 1 km^2 pixel. The time series of *fAPAR* and *LAI* were smoothed by the TIMESAT software (Jönsson & Eklundh, 2002) and interpolated between available cloud free images. In total, 682 MERIS images covering the years from 2003 to 2011 were used;
- Daily meteorological data from the BaltAN65+ regional 11 km^2 reanalysis database resampled into 1 km^2 grid over Estonia (total cloudiness, average (and minimum) air temperature, water vapour pressure deficit).

For years 2003–2011 daily GPP and NPP values and yearly sums were produced for all pixels of Estonian land on 1 km^2 grid, except for pixels classified as wetland or settlement. Year 2007 was problematic, since there were two large gaps during the vegetation period where there was no meteorological data available.

In addition, inputs to calculate the yearly NPP include the daily (10-day) values of temperature, LAI, and annual maximum value of leaf mass (LAI/SLA).

Model calculations.
Preparation of necessary inputs

1 km^2 grid for GPP/NPP calculations

The modelling grid covers entire Estonia including a 5 km buffer zone at the borders. The grid is based on the ETRS89 Lambert azimuthal equal-area (LAEA) projection coordinate reference system. The spatial resolution of the grid is 1 km. The modelling grid consists of 370 columns and 255 rows creating a total of 94350 grid cells. The top left corner coordinates of the grid are [x,y] = [5003000, 4176000]. All model inputs were resampled onto this grid for model calculations.

Land cover data

Land cover map of Estonia was produced as one of the model inputs (Fig. 3). This was achieved using satellite images as land cover classification inputs. Due to the big differences in spatial resolution of the mod-

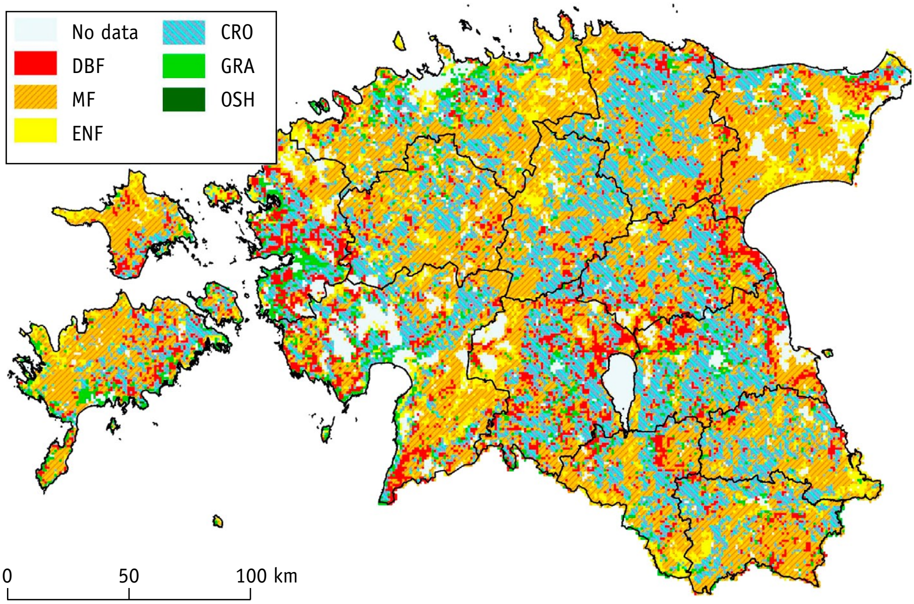

Figure 3. The land cover map of Estonia used in the modelling. The map has been transformed into L-Est'97 coordinates. DBF – Deciduous Broadleaf Forest, MF – Mixed Forest, ENF – Evergreen Needleleaf Forest, CRO – Cropland, GRA – Grasslands, OS – Open Shrublands. Marshes/Fens, Bog, Peat Extraction Areas, Settlements and Other Land are not shown.

Joonis 3. Mudelarvutusteks kasutatud Eesti maakaatekaart, teisendatuna L-Est'97 koordinaatidesse: DBF – heitlehelised lehtmetsad, MF – segametsad, ENF – igihaljad okasmetsad, CRO – põllumaa, GRA – rohumaa, OS – avatud põõsastik.

elling grid and the satellite images, land cover data generation was divided into two main parts: land cover classification map production from DMCii SLIM-6-22 satellite images and resampling that classification map onto the much coarser modelling grid. The main inputs to the classification were two DMCii images (8 June 2011 and 28 June 2011), covering together the whole Estonia.

In addition, some ancillary datasets were also used: the CORINE 2006 land cover classification map, Estonian soil map, orthophotos, vector layers of infrastructure (highways, roads, train tracks, but streets in urban areas were excluded), buildings layer from Regio Ltd database, also vector layers of cropland, grassland, mixed cropland/grassland and semi-natural areas provided by the Estonian Agricultural Registers and Information Board (PRIA).

The two satellite images were classified separately and then combined into a single classification image. Maximum likelihood classification was used as the main classification algorithm. The land cover map produced from the satellite images has a spatial resolution of 22 m, CRS of WGS84 / UTM Zone 34N and distinguishes between the following land cover classes: Deciduous Broadleaf Forest, Mixed Forest, Evergreen Needleleaf Forest, Cropland, Grasslands, Open Shrublands, Marshes/Fens, Bog, Peat Extraction Areas, Settlements and Other Land. Further, the high-resolution land cover map was resampled into the 1 km^2 grid.

Marshes/Fens, Bog, Peat Extraction Areas, Settlements and Other Land were excluded from the GPP/NPP simulation.

Meteorological data

Data used. The meteorological data used for the creation of model inputs comes from two sources: the EMHI/UT BaltAn65+ meteorological reanalysis dataset and EMHI's HIRLAM model. This is because the BaltAn65+ dataset covers the years 1965–2005, thus covering the period of 2003–2005 of this modelling procedure. EMHI's HIRLAM model was used for the generation of the reanalysis data. The meteorological inputs needed for EST_PP model inputs creation were:

- Temperature
- Relative humidity
- Total cloud cover

These parameters were supplied with a six hour time interval four times a day at 00, 06, 12 and 18 hours UTC (depending on the time of the year this is either one or two hours less than the local time in Estonia).

Data processing. The meteorological model used by EMHI is run on a spherical Earth rotated coordinate system (south pole at –30° lat, 0° lon), which maps the modelling area and Estonia near the equator. The spatial resolution of the model is 0.1° which equals to about 11.1 km. The meteorological fields were extracted from the original files, reprojected to the LAEA reference system and resampled into the 1 km^2 grid used in the EST_PP model. Nearest neighbour resampling was applied.

Daily average air temperature was calculated from all four temperature values for that day. Daytime average water vapour deficit was calculated by averaging the water vapour deficit fields for 06, 12 and 18 hours UTC, calculated using the temperature and relative humidity fields of the according times. Daytime average total cloud cover fraction was calculated from total cloud cover fields of 06, 12 and 18 hours UTC. This way images of the daily average temperature data, daytime water vapour deficit and daytime average cloud cover fraction were created.

Determination of fAPAR

Data used. MERIS satellite images were used for the creation of fAPAR time series. Potential MERIS images were identified and ordered using the EOLi client (Earth Observation Link, the European Space Agency's client for Earth Observation Catalogue and Ordering Services).

Data processing. ESA's Basic ERS & Envisat (A) ATSR and Meris Toolbox (BEAM) software was used for the first data processing steps. The BEAM MERIS L1b Radiometry Correction data processor was used for radiometric re-calibration, smile-effect correction and equalization (for removal of MERIS detector-to-detector systematic radiometric differences). Then MERIS TOA-VEG processor from MERIS Vegetation Processors (plug-in of BEAM) was used to calculate images of fAPAR from the corrected MERIS data. As the last processing step in BEAM, the data was reprojected to ETRS89-LAEA projected CRS with the top left corner coordinates to coincide with the GPP model's top left corner coordinates. Bilinear resampling was chosen as the resampling algorithm. Next the data was resampled to the coarser model grid taking the average of all MERIS pixels in the respective modelling grid cell.

Overall 682 fAPAR images were used which gives an average of 76 images per year. As TIMESAT algorithm (Jönsson & Eklundh, 2002) was used for fAPAR time series creation, it was necessary to generate time composites from the individual daily fAPAR images. This helped to avoid having a large number of big gaps in the time series that TIMESAT had problems processing. The maximum value in each time interval was chosen as the representative value for that period/composite. 10-day composites were used in model calculations.

TIMESAT was used to smooth the time series of time composites of fAPAR and fill the gaps of missing data (some gaps were left after time compositing due to the cloudy weather conditions common to Estonia and to the latitudes). TIMESAT allows a choice between different smoothing algorithms each with editable parameters for time series creation. With the land cover map, it was possible to use different smoothing algorithms and parameters for different land cover classes. Two different algorithms were used for fAPAR time series creation for this model: Savitzky-Golaj filtering was used for pixels belonging to Cropland land cover class and double logistic functions fit was used for the remaining land cover classes. TIMESAT also allows the use of quality flag data to assign weights to each pixel for every time step. This helped for example to eliminate pixels corresponding to cloudy conditions (when cloud data/quality flag data was available). An IDL procedure was written to generate quality data for fAPAR time composites which accounted for cloud contaminated pixels (erroneously low values of fAPAR). Once all the algorithms, parameters and quality data were ready, images of smoothed fAPAR time series were generated and ready to use as model inputs.

Tree ring data

Increment cores from living trees of Scots pine (Hordo *et al.*, 2009; Hordo *et al.*, 2011), Norway spruce and birch stands were collected. Stands were selected before fieldwork from State Forest Service database by the dominating tree species, stand age and more common forest site type (growth is limited or advanced by site conditions). The distribution of collected samples was not even between the counties. All cores were taken from mature stands, because length of tree ring series is important for cross-dating (matching the pattern and allowing assertion of annual resolution to provide exact calendar year for every tree ring in sample). In total 1083 pine, 725 spruce and 705 birch trees were cored. From each selected tree, two increment cores in opposite directions were taken using an increment borer at 1.3 m above the ground. Annual ring-widths were measured with an accuracy of 0.01 mm using the LINTAB tree-ring measuring table with the computer program TSAP-Win Scientific Version 0.59 (Rinn, 2003).

Tree ring width is a linear measure of the trunk increment. To transform the tree ring width ΔR into volume increment ΔM values, the following formulas were used (Vaus, 2005) :

$$M = G\,H\,F\,, \tag{18}$$

where G is the basal area (m^2/ha), H – average tree height, F – the form factor, calculated as:

$$F = b_0 + \frac{b_1}{H} + b_2\sqrt{H} + b_3 ln(H)\,, \tag{19}$$

where b_i are the species specific coefficients (Vaus, 2005). Assuming that there is a single tree size class:

$$G = \pi D^2 N/4\,, \tag{20}$$

where D=2R is the breast-height trunk diameter (m), N is the stand density (number of trees per ha). Volume increment may be approximately calculated as:

$$\Delta M = \pi(R+\Delta R)^2(H+\Delta H)NF - \pi R^2 HNF =$$
$$= \pi NF((R+\Delta R)^2(H+\Delta H) - R^2H) =$$
$$= \pi NF(2RH\Delta R + R^2\Delta H + 2R\Delta H\Delta R + \Delta R^2\Delta H$$
$$\approx \pi NF(2RH\Delta R + R^2\Delta H)\,. \tag{21}$$

In order to calculate the volume increment from the tree ring width, estimates for the stand density, form factor, tree height, breast-height diameter and height increment have to be known. In the calculations of volume increment from tree ring widths, average values of these parameters from Järvselja (2011) forestry database were used. Finally, volume increments were transformed into carbon units as the wood density and percentage of carbon in wood was known to be 50%.

MODIS GPP/NPP product

For comparison, MODIS NTSG (Numerical Terradynamic Simulation Group) yearly GPP/NPP product data (MOD17) for Estonia were downloaded from the MODIS

LP DAAC webpage (MODIS, 2012) and resampled from original sinusoidal projection into ETRS89 LAEA 1 km^2 grid.

Results of simulation

The simulated NPP and GPP values for the used land cover types by EST_PP and MODIS algorithms are compared in Tables 2 and 3. Table 2 presents the values averaged over the whole period of the simulation, from 2003 to 2011, while Table 3 shows the values separately for each year.

The 'climatological' GPP map (Fig. 4) of Estonia, obtained as an average GPP over the whole period of simulation shows a distinct regional pattern with elevated values at the western shoreline. One part of

Table 2. EST_PP and MODIS NPP and GPP values (kgC/m^2/year) by land cover classes averaged over the whole period considered. For abbreviations of land cover classes, see Table 1.

Tabel 2. Vaadeldava perioodi NPP ja GPP Eesti keskmised väärtused (kgC/m^2/aasta) maakatteklasside kaupa. Maakatteklasside tähistused vt Tabel 1.

Product	NPP		GPP	
Model	EST_PP	MODIS	EST_PP	MODIS
DBF	0.547	0.542	0.828	0.977
MF	0.503	0.556	0.787	1.011
ENF	0.333	0.553	0.734	1.012
CRO	0.427	0.472	0.728	0.808
GRA	0.326	0.508	0.629	0.889
OSH	0.259	0.513	0.599	0.901

Table 3. EST_PP and MODIS average yearly NPP values (kgC/m^2/year) over Estonia by land cover classes. For abbreviations of land cover classes, see Table 1.

Tabel 3. Maakatteklasside Eesti keskmised NPP väärtused (kgC/m^2/aasta) aastate kaupa. Maakatteklasside tähistused vt Tabel 1.

		DBF	MF	ENF	CRO	GRA	OSH
2003	EST_PP	0.530	0.478	0.312	0.396	0.320	0.229
	MODIS	0.518	0.556	0.553	0.459	0.479	0.498
2004	EST_PP	0.542	0.479	0.299	0.379	0.295	0.212
	MODIS	0.550	0.580	0.570	0.477	0.509	0.519
2005	EST_PP	0.603	0.552	0.385	0.483	0.385	0.263
	MODIS	0.569	0.584	0.583	0.488	0.540	0.537
2006	EST_PP	0.409	0.413	0.277	0.325	0.272	0.214
	MODIS	0.500	0.481	0.530	0.412	0.448	0.474
2007	EST_PP	–	–	–	–	–	–
	MODIS	0.549	0.560	0.566	0.494	0.534	0.529
2008	EST_PP	0.551	0.491	0.314	0.404	0.317	0.223
	MODIS	0.586	0.612	0.590	0.511	0.553	0.536
2009	EST_PP	0.585	0.516	0.340	0.427	0.339	0.271
	MODIS	0.583	0.591	0.571	0.502	0.542	0.545
2010	EST_PP	0.533	0.518	0.350	0.454	0.358	0.285
	MODIS	0.484	0.488	0.485	0.429	0.465	0.472
2011	EST_PP	0.630	0.595	0.413	0.519	0.403	0.319
	MODIS	–	–	–	–	–	–
Average	EST_PP	0.547	0.503	0.333	0.427	0.326	0.259
	MODIS	0.542	0.556	0.553	0.472	0.508	0.513
Standard deviation	EST_PP	0.072	0.058	0.048	0.066	0.047	0.040
	MODIS	0.038	0.048	0.034	0.035	0.040	0.029

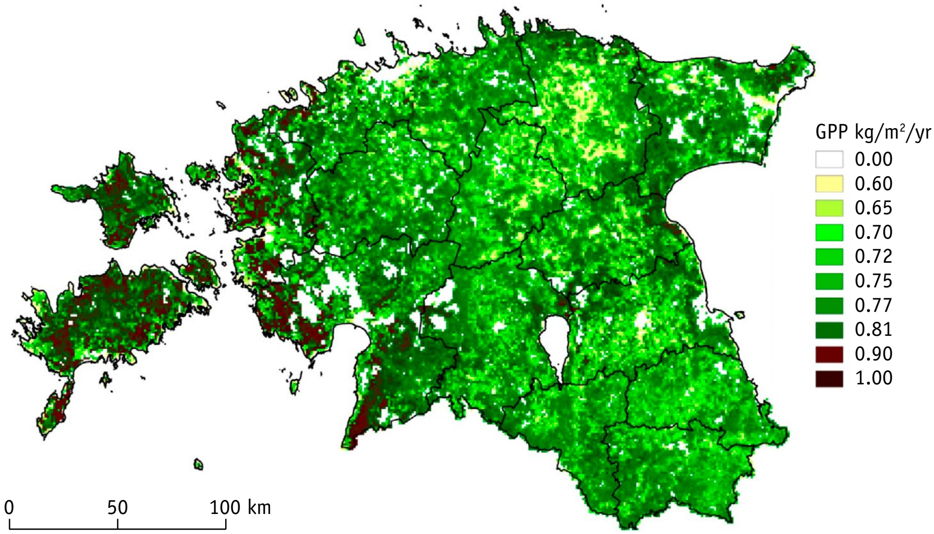

Figure 4. The map of GPP of Estonian land pixels as simulated by EST_PP model (averaged over 2003–2011). Borders of Estonian counties are shown by black line.

Joonis 4. Üle aastate 2003–2011 keskmistatud Eesti maismaa GPP kaart EST_PP mudelarvutuse tulemusena. Eesti maakondade piirid on näidatud musta joonega.

the GPP variability is caused by local and yearly differences in meteorological variables; while another part is influenced by the regional distribution of different land cover classes and differences in fAPAR. The map shows that meteorological conditions in Estonia are somewhat more favourable for plant productivity on the islands and coastal regions, compared with the inland. Qualitatively similar regional differences are present in the average NPP map. A rather similar 'climatological' regional distribution appears in the MODIS GPP product (Eenmäe, *et al*., 2011).

Comparison with MODIS GPP/NPP product and Estonian statistical data

Comparison with the MODIS GPP/NPP product

In spite of the similarity between MODIS and our GPP/NPP models, the simulation results show differences between the values on the local and whole country scales (Fig. 5). Many of the differences are expected, since

- MERIS images are used instead of the MODIS images to determine the fAPAR and LAI inputs, the algorithms used in the MODIS and MERIS fAPAR derivation are different;
- PAR is estimated by a different method;
- Temperature reduction factor is estimated by a different algorithm. If averaged over a growing season, the temperature reduction factor (Eq. 5) is systematically less than the similar seasonal average in the MODIS GPP/NPP algorithm (Eq. 5a);
- Land cover maps have been determined by a different method and from different source data and do not fully coincide;
- Regional and much higher resolution (11 × 11 km) BaltAN65+ (HIRLAM) meteorological reanalysis data is used instead of the global reanalysis data at a 1.25° × 1° resolution by NASA DAO in the MODIS algorithm.

The average over all Estonian land pixels and considered years GPP was 0.745 kgC/

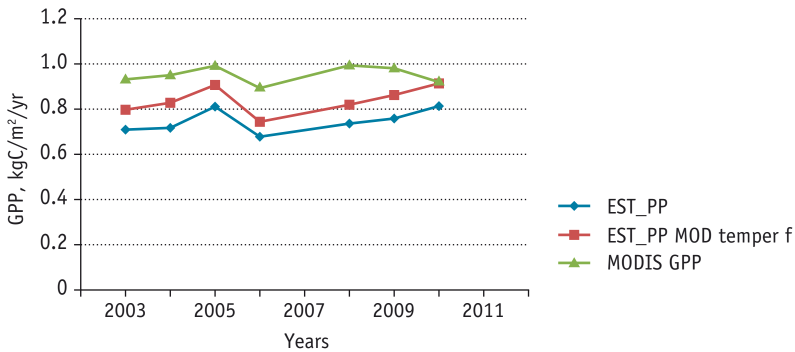

Figure 5. Comparison between Estonian land average GPP simulated by three methods: original MODIS GPP product, our model (EST_PP) and EST_PP model with the temperature limiting factor from the MODIS GPP algorithm (Eq. 6a). Pixels corresponding to settlements and wetland have been excluded from the analysis.

Joonis 5. Eesti maismaa keskmise GPP võrdlus, arvutatuna kolme erineva meetodiga: MODIS GPP originaaltulem, meie mudel (EST_PP) ja EST_PP koos MODIS'e GPP algoritmi temperatuuri mõjuteguriga (valem 6a). Asulatele ja märgaladele vastavad pikslid on analüüsist välja jäetud.

m^2/year using our EST_PP model, 0.837 when EST_PP with the MODIS temperature reduction functions was used and 0.953 kgC/m^2/year when applying the original MODIS algorithm. Larger differences between these values were found in the western islands of Estonia and in the coastal counties, while the inland differences between counties using these three methods were less obvious. Hence, the difference in Estonian average was 0.837–0.745 = 0.092 kgC/m^2/year when applying different temperature reduction factors. The difference 0.953–0.837 = 0.116 kgC/m^2/year was caused by other factors, such as differences in values of PAR and meteorological variables and in land cover classification pixels as well as by the possible differences between MERIS and MODIS fAPAR.

Although several studies have shown a good agreement between MODIS and MERIS fAPAR estimates, a study of the Iberian peninsula (Seixas *et al.*, 2007) has found that MODIS fAPAR values are systematically higher compared with the values from MERIS.

Figure 6 demonstrates that the two models, MODIS and EST_PP, also show systematic differences in the simulated GPP and NPP between the land cover classes. For instance, average NPP estimates are almost the same for the two models for deciduous forest pixels, however, for evergreen needleleaf forest and grassland pixels, the MODIS-simulated values considerably exceed the values simulated by EST_PP.

Comparison with the Estonian National statistical data

Among other data Estonian National statistical databases (e.g., Statistical Yearbook of Estonia, 2013 (and from other years); Yearbook Forest, 2009) provide estimates of the agricultural yield and yearly volume increment in forests.

In a typical Yearbook Forest, there are two tables where volume increment data are given, Estonian averages by dominant tree species and ownership category (state-owned, private) and similar averages by counties. To compare with the results of our model simulation, we need to know how the volume increment data in the yearbook has been obtained. State average volume increment numbers have been derived from the statistical National Forest Inventory (NFI) data using the measured data from previous five years. Species specific regres-

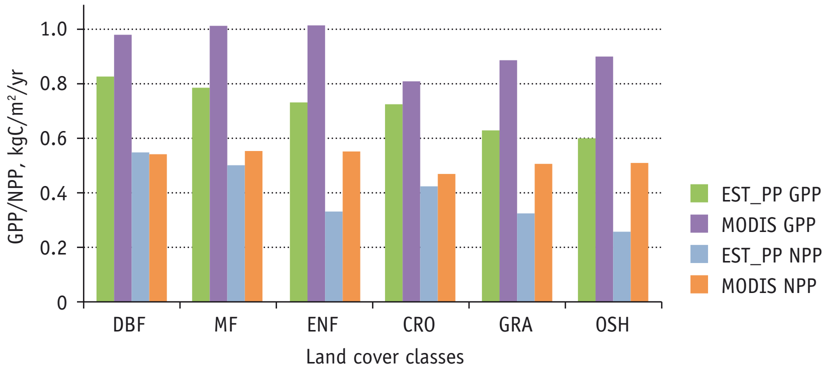

Figure 6. GPP and NPP values for main land cover classes from EST_PP and MODIS products, averaged over the modelling period. Deciduous Broadleaf Forest (DBF), Mixed Forest (MF), Evergreen Needleleaf Forest (ENF), Cropland (CRO), Grassland (GRA) and Open Shrubland (OSH).

Joonis 6. Peamiste maakatteklasside GPP ja NPP arvutatuna EST_PP ja MODIS'e tulemist ning keskmistatutena üle kogu vaadeldava ajavahemiku. Laialeheline lehtmets (DBF), segamets (MF), igihaljas okasmets (ENF), põllumaa (CRO), rohumaa (GRA) ja avatud põõsastik (OSH).

sion equations derived by P. Kohava (Metsa korraldamise juhend, 2006) relating the yearly increment to stand age, site index and stock density have been used to calculate yearly stem volume increments. This means that the Estonian yearly increment data in Yearbook Forest represent average estimates from five previous years and are thus smoothed. Even more smoothed are the volume increment estimates for individual counties, since they are also calculated by the same regression by Kohava, but using the bulk forest inventory data containing in Estonian Forest Register. In the Forest Register, the data can be up to ten years old.

For forests, the volume increment can be converted into trunk biomass increment by knowing the average wood density and into carbon (C) increment by assuming that there is ~50% of C in wood. When the average NPP values of forests are compared with the annual increment of C in tree trunks, considerable differences between these values are found. However, these two values are not directly comparable, since to get the NPP value, carbon allocated into trunks, the C contribution allocated to roots, branches, leaves, understory plants and all components of respiration have to be considered. According to Gower *et al.* (2001) and Turner *et al.* (2004), NPP values should be approximately three times larger than the mean annual increment of C in trunks, when averaged over the whole lifetime of a forest. They suggested the following generalized empirical linear relations:

$ANPP = 0.042 + 2.34MAI$, for evergreen species,

$ANPP = 0.080 + 2.62MAI$, for deciduous species, (22)

and

$NPP = 0.114 + 1.21ANPP$.

Where MAI is the mean annual increment of C in trunks (kgC/m^2/year), $ANPP$ (kgC/m^2/year) is the aboveground NPP and NPP is the total NPP (below-ground part included). When assuming that regressions in Eq. 22 hold true for Estonia, the Estonian land average MODIS-simulated NPP values appear to be rather realistic (Fig. 7).

Some of features in NPP distribution over the years, such as the significant drop of productivity in 2006 appear in both, MODIS and EST_PP model-simulated NPP values (Fig. 7). Compared with its neighbouring years, summer 2006 was

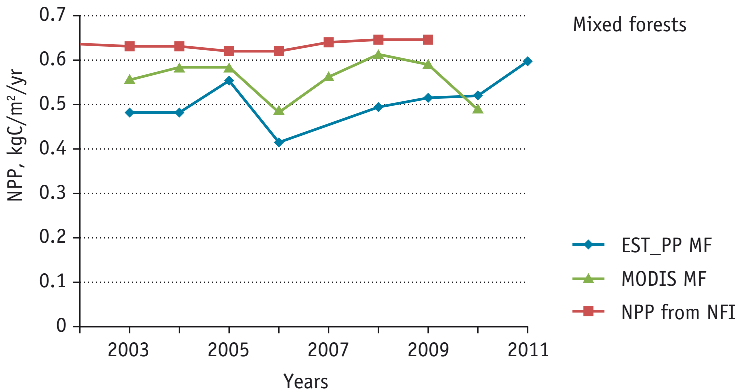

Figure 7. Comparison of average yearly NPP estimates of mixed forest (MF) pixels, simulated by the EST_PP model, original MODIS NPP product (MF) and NPP of Estonian forests derived from national forest statistics (NFI). NPP from NFI was estimated by using regressions Eq. 22 relating the annual trunk increment to aboveground and total NPP from Turner *et al.* (2004).

Joonis 7. Segametsade (MF) aastakeskmised NPP hinnangud, arvutatutena EST_PP mudeli ja MODIS'e NPP tulemist, võrrelduna Eesti metsade keskmise NPP hinnanguga, mis on tuletatud riikliku statistika (NFI) andmetest. Viimase hinnangu tuletamiseks kasutati regressioone (valem 22), mis seovad aastase tüvemassi juurdekasvu maapealse ja summaarse NPP väärtusega (Turner et al., 2004).

exceptionally sunny, but dry and thus unfavourable for plant production. With respect to NPP values derived from the data in Yearbook Forest, one has to keep in mind that the coefficients of regression equation to calculate the yearly increment remain the same for all years, independently of the meteorological conditions for the particular year.

The NPP values of cropland pixels simulated by the two models are compared with the NPP derived from the yield data of agricultural fields by Estonian national statistics on Fig. 8. Although, there are some features that are common in the simulated and yield data, in general the NPP changes from year to year have not been reproduced adequately by these models. With the agricultural yield, it is also important to know that the simulated GPP/NPP values should rather be interpreted as potential yield, so the losses in real yield due to unfavourable weather conditions during the harvesting period are not taken into account. In some years, such as 2012, when the autumn was extremely rainy, these losses could be considerable. As it appeared for forest pixels, a similar minimum of NPP was also observed in 2006 in the agricultural crop production. EST_PP has predicted a gradual increase in productivity in years 2008–2011 that was not confirmed by the national statistics records. The simulated NPP values by the MODIS algorithm considerably exceed those derived from the national statistics, even if the harvest index (the weight of a harvested product as a percentage of the total (typically aboveground) plant weight of a crop) has been taken into account. A part of the difference between the curves on Fig. 8 is caused by the role of belowground carbon allocated to roots and not taken into account when estimating the NPP from yield statistics data.

In addition to the country-average estimates of NPP, it is possible to look at the regional differences in yearly NPP. MODIS-simulated NPP shows that the productivity in the islands and western counties of Estonia should be larger than for

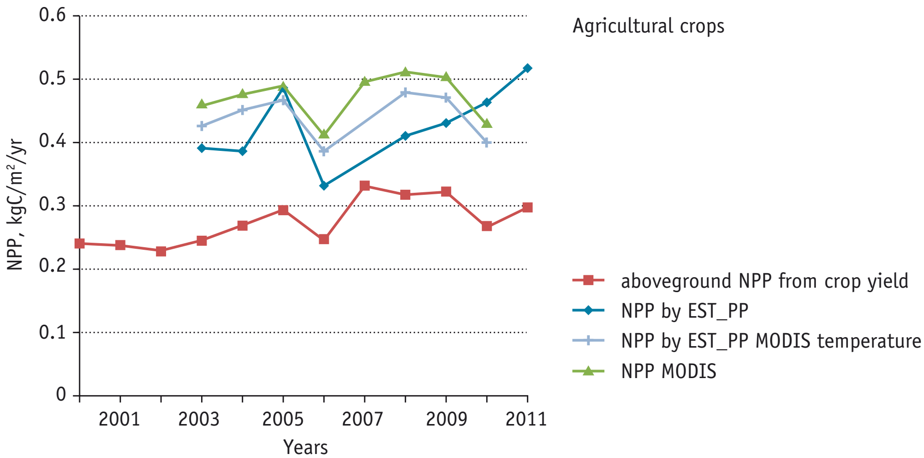

Figure 8. Comparison of yearly average NPP for cropland pixels as simulated by the EST_PP and MODIS NPP models with the national average aboveground NPP for agricultural fields as estimated from the national statistics data.

Joonis 8. Põllumaa pikslite aastakeskmiste NPP-de võrdlus. Mudelarvutused EST_PP ja MODIS'e NPP mudelite abil ja (NPP maapealse osa) hinnang, tuletatuna ametliku statistika saagikuse andmetest.

the inland (see also Eenmäe *et al.*, 2011). When to plot the county-wide average NPP as simulated by the two models against Eastings of county centroids, the MODIS original NPP shows the steepest negative W-E trend while the EST_PP a moderate negative trend. However, the national statistical data of tree trunk volume increment and agricultural yield indicate just opposite trend, showing an increase of forest productivity towards inland. For instance, in 2010, the following regression equations between the forest NPP (y, kgC/m^2/year) and county centroid Easting in L-Est'97 (x, km) were found:

$y = 0.00037x + 0.378$, $R^2 = 0.492$, for national statistical data,

$y = -0.00020x + 0.714$, $R^2 = 0.541$, for EST_PP,

$y = -0.00094x + 1.041$, $R^2 = 0.831$, for MODIS NPP.

Similar problems arise with the North-South trends of forest productivity, where national forest statistics data yield a decreasing trend of NPP towards North while EST_PP-simulated values show an increasing trend. The same pattern is repeated for the simulated NPP compared with the yield of agricultural crops from national statistics. This means that both NPP simulation algorithms, particularly the MODIS algorithm, are not able to adequately describe the NPP regional differences in Estonia, even if the mean NPP estimates over forested area seem to have a reasonable fit. The present versions of MODIS NPP and EST_PP are able to consider the effects of meteorological factors (incoming radiation, air temperature and humidity), however, these models ignore the local differences in soil fertility and water-holding capacity.

Concerning the choice of the temperature reduction factor, we can conclude that Eq. 5 gives more acceptable results concerning the east-west GPP and NPP trends compared with Eq. 5a. However, due to systematic differences between the averaged values of the temperature reduction factor over the vegetation period, simulations with Eq. 5 result in systematic underestimation of GPP and NPP products compared with Eq. 5a. Thus, a compensation of using higher LUE ε values may be needed together with applying Eq. 5. It is evident that different temperature reduction factors are not the only cause of systematic differences between the EST_PP and MODIS NPP algorithms.

We also studied the pixel-wise correlation between GPP and NPP estimates as produced by MODIS and EST_PP models (Table 4). Various differences in these two algorithms and in the input information can cause reduction of the correlation coefficient. The correlations appeared to be rather low in the northern counties, such as Ida-Virumaa and Lääne-Virumaa. One of the reasons for such low correlation could be caused by differences in the meteorological input parameters on the coarse grid of the MODIS algorithm compared with much finer grid in the EST_PP algorithm. At the same time for some counties (Põlvamaa, Võrumaa) the correlation coefficients reach reasonably high values. The correlations were systematically higher for NPP compared with GPP. Evidently, the respiration terms in the NPP algorithm reduce the differences between the two algorithms.

Table 4. Coefficients of correlation by counties of Estonia between the simulated values of NPP and GPP by the MODIS and EST_PP algorithms. The correlation was studied over the pixels in each county having the same land cover type in both algorithms, number of common pixels is indicated in the Table.

Tabel 4. Korrelatsioonikordajad MODIS'e ja EST_PP algoritmide NPP ja GPP väärtuste vahel Eesti maakondades. Korrelatsioon arvutati üle kõigi pikslite, millel oli sama maakatteklass mõlemas algoritmis, ühiste pikslite arv on tabelis toodud.

County	NPP	GPP	no of common pixels
Harjumaa	0.264	0.192	1527
Hiiumaa	0.420	0.273	436
Ida-Virumaa	0.114	0.078	1376
Järvamaa	0.393	0.247	956
Jõgevamaa	0.423	0.235	854
Läänemaa	0.519	0.471	403
Lääne-Virumaa	0.145	0.073	1332
Pärnumaa	0.374	0.226	1375
Põlvamaa	0.805	0.710	523
Raplamaa	0.504	0.311	1143
Saaremaa	0.399	0.270	1001
Tartumaa	0.553	0.237	763
Valgamaa	0.663	0.528	689
Viljandimaa	0.535	0.266	830
Võrumaa	0.820	0.751	754

MODIS algorithm overestimates the GPP contrasts between the coastal and inland counties. This can be well understood, if to analyze how the MODIS GPP/NPP algorithm works. This effect comes mainly from the used meteorological reduction factors.

With respect to GPP and NPP of crop pixels, Estonian national statistics is based on real yield data and thus can show the real variation of crop yield from year to year due to the weather. When comparing the simulated NPP values to the NPP estimates derived from the yearly yield data of different agricultural crops, it seems that MODIS NPP product overestimates the productivity. At the same time the variation of the simulated crop NPP from year to year does not fully agree with the data presented in the national statistical yearbooks, only the minimum on a dry year 2002 is notable in the simulations and real yield.

The present method of calculating the yearly estimates of trunk wood increment in national forest statistics is not able to catch the differences between years caused by meteorological factors. So, it would be desirable that yearly increment regressions take into account the measured diameter and height increments of the particular year.

Comparison with the results of tree ring analysis

The Estonian average yearly volume increments as recalculated from the tree ring width data and transformed into the NPP units kgC/m^2/yr that are compared with the Estonian averages of simulated NPP values by EST_PP and MODIS NPP models in Fig. 9 and 10. For comparison, Estonian average NPP estimates derived from the data in forest yearbooks are given using the statistical NFI data and Forest Register data. Birch year ring data are taken as a representative of deciduous forests. For coniferous forests, both the spruce and pine tree ring data are shown. The depression of growth in the dry year of 2006 can be seen in the simulated NPP curves as well as in the tree ring data. Both the simulated NPP values are lower than values estimated from the forestry and tree ring data for the same years. The data in the Forest Register should be treated as averages over several years (up to 10 years) and NFI data as averages over previous five years. So, the NPP estimates on these figures based on forestry data have been smoothed over several years and do not vary much from year to year, thus should not be compared with the rest of the data on yearly basis. We see that the NPP estimates derived from the tree ring data are systematically higher compared with the estimates provided by other methods. It is possible that the used method to recalculate NPP from the tree ring widths is causing some systematic overestimation, or the stands or trees where the tree ring widths were measured, were selected with systematically larger increments than should be in the county or for Estonian average. With respect to conifers, it is evident that the EST_PP model systematically underestimates NPP for coniferous stands. It seems that the value of LUE coefficient ε or of coefficients responsible for respiration for conifers should be revised.

We also compared the county-average NPP values as simulated by the MODIS and EST_PP algorithms with the results of tree ring width measurements from the same county and year. The results of linear regression between these variables, showing the ability of models to predict the variability of NPP from year to year, are given in Tables 5 and 6.

We see that the coefficients of determination of linear regression are not high. It is apparent that the simulated changes in NPP correlate better with the tree ring width for inland counties. MODIS NPP tends to be related to the tree ring data slightly bet-

Table 5. Spruce. Linear regression of tree ring width (y, 0.01mm) on MODIS NPP for coniferous forest pixels (x, kgC/m^2/year) in different counties of Estonia.

Tabel 5. Lineaarne regressiooniseos kuuse aastarõnga laiuse (y, 0,01mm) ja MODIS'e NPP mudeliga okasmetsa pikslitele arvutatud NPP vahel (x, kgC/m^2/aasta) erinevates maakondades.

County	Regression equation	Coefficient of determination, R^2
Harjumaa	y = 706.18x – 153.8	0.1649
Ida-Viru	y = 450.99x – 40.279	0.3359
Järvamaa	y = 589.45x – 99.872	0.2382
Jõgevamaa	y = 567.48x – 91.265	0.2169
Pärnumaa	y = 178.75x + 58.484	0.0489
Põlvamaa	y = 1146.9x – 437.89	0.5237
Raplamaa	y = 478.28x – 124.49	0.2521
Tartumaa	y = 446.85x – 65.904	0.5814
Valgamaa	y = 1201.2x – 424.12	0.7418
Viljandimaa	y = 746.26x – 246.89	0.5722
Võrumaa	y = 643.16x – 190.6	0.6904

Table 6. Spruce. Linear regression of tree ring width (y, 0.01mm) on EST_PP for coniferous forest pixels (x, kgC/m^2/year) in different counties of Estonia.

Tabel 6. Lineaarne regressiooniseos kuuse aastarõnga laiuse (y, 0,01mm) ja EST_PP mudeliga okasmetsa pikslitele arvutatud NPP vahel (x, kgC/m^2/aasta) erinevates maakondades.

County	Regression equation	Coefficient of determination, R^2
Harjumaa	y = 495.09x + 57.385	0.1073
Ida-Viru	y = 510.25x + 4.15	0.3376
Järvamaa	y = 273.36x + 121.37	0.0507
Jõgevamaa	y = 293.22x + 101.2	0.0615
Pärnumaa	y = 244.75x + 83.484	0.2120
Põlvamaa	y = 669.94x - 59.149	0.3087
Raplamaa	y = 207.33x + 67.496	0.0795
Tartumaa	y = 338.09x + 45.945	0.3420
Valgamaa	y = 545.05x + 44.878	0.4983
Viljandimaa	y = 364.37x + 38.895	0.3141
Võrumaa	y = 281x + 50.773	0.2557

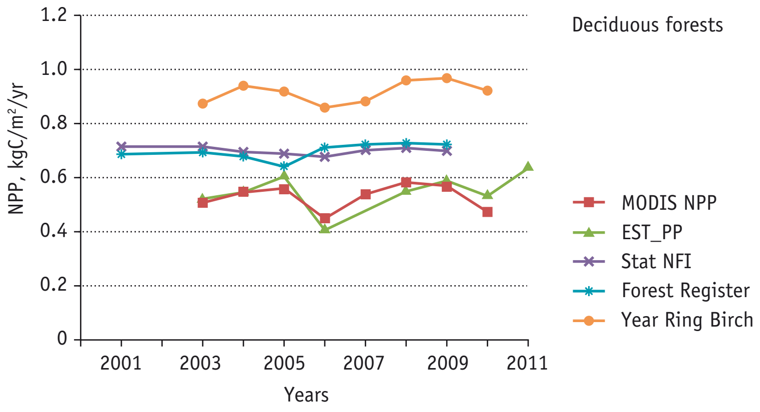

Figure 9. Yearly changes of NPP of deciduous forests as estimated by different methods: MODIS NPP as an all-Estonian average over all deciduous forest pixels, similar estimates by the EST_PP model, recalculated from the all-Estonian gross annual volume increment data from Yearbook Forest by statistical NFI and from the Forest Register, respectively, and recalculated from year ring data for birch averaged over all available measurements in different counties.

Joonis 9. Lehtmetsade NPP muutused aastatega hinnatuna erinevate meetodite poolt: MODIS'e NPP keskmine üle kõigi lehtmetsade pikslite, samasugune keskmine EST_PP mudelarvutustest, ümberarvutatud aastaraamatu „Eesti Mets" statistilise metsainventuuri (NFI) ja Metsaregistri tagavara juurdekasvu üle-Eestilistest andmetest ning arvutatud kase aastarõngaste mõõtmistulemustest, keskmistatuna üle kõigi mõõtmiste erinevates maakondades.

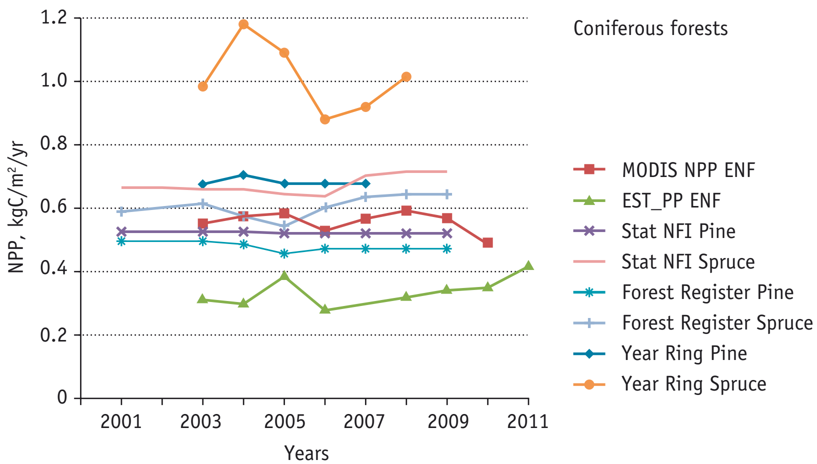

Figure 10. Yearly changes of NPP of coniferous forests as estimated by different methods: MODIS NPP as an all-Estonian average over all coniferous forest pixels, similar estimates by the EST_PP model, recalculated from the all-Estonian gross annual volume increment data from Yearbooks Forest by statistical NFI and from the Forest Register, respectively, and recalculated from year ring data for pine and spruce averaged over all available measurements in different counties.

Joonis 10. Okasmetsade NPP muutused aastatega hinnatuna erinevate meetodite poolt: MODIS'e NPP tulemi keskmine üle kõigi okasmetsade pikslite, samasugune keskmine EST_PP mudelarvutustest, ümberarvutatud aastaraamatust „Eesti Mets" statistilise metsainventuuri (NFI) ja Metsaregistri üle-Eestilise tagavara juurdekasvu andmetest ning arvutatud kuuse ja männi aastarõngaste mõõtmistulemustest, keskmistatuna üle kõigi mõõtmiste erinevates maakondades.

ter than the NPP values simulated by the EST_PP model. Similar results appeared for deciduous forest pixels compared with the existing birch tree ring widths. A far more systematic comparison of the tree ring width and height increment data with the results of NPP simulation is needed in the future.

Discussion and further perspectives

The most difficult problem with the GPP/NPP models based on the Monteith relation is that the validity of the basic principle has not been sufficiently tested, at least at the regional and local levels. It could well be, that on the global level where different climatic regions are compared, the Monteith relation-based model works reasonably well, even if the application of the relation at a local scale could be problematic. If the method works locally at an individual stand level, we must expect an acceptable correlation between the seasonal sum of fAPAR as estimated from higher resolution satellite images and volume increment. Or when selecting stands dominated by a certain species, we could expect a correlation between the midsummer fAPAR and volume increment.

The suggested GPP/NPP model has a clear potential to produce yearly estimates of the productivity and CO_2 sequestration by forests and agricultural crops at the county and state levels. As a result, the parts in national CO_2 reports that consider the carbon balance of vegetation could well be based on such model calculations. However, so far the GPP/NPP models and the underlying light use efficiency (LUE) concept have not been sufficiently validated in regional Estonian conditions, so presently the simulation results could have a considerable uncertainty. Nevertheless, these models have the potential to be able to quantitatively consider the effect of key meteorological factors and the time course of vegetation phenology on the vegetation productivity, as well as carbon sequestration with the aid of satellite images. It is expected that after the differences in soil fertility and/or water holding capacity have been included into the model, the model performance, at least its regional (county-level) performance, should improve.

The only stand variables entered to the present model as inputs are fAPAR and LAI. In fact, LAI is used only to calculate respiration and allocation of photosynthetic products of all organs. Stand age and site fertility as such are ignored. Indeed, these factors may not be needed if considerable areal averages and global processes are considered. However, if the LUE concept based NPP models are applied at a stand level, the models have to be refined to include at least stand age and site fertility. In addition to the principal problem of applicability of the Monteith relation to every individual stand and for shorter periods of time (day, week, month), another difficulty arises how to get the yearly courses of fAPAR and meteorological factors for a stand. Diminishing the pixel size in model calculations would cause larger uncertainty of the inputs derived from the satellite images, such as the fAPAR and LAI estimates. As a result, the temporal courses of fAPAR and LAI would become rougher and would need more smoothing. Another important point is that higher resolution images are typically more expensive and the revisiting capability of higher resolution sensors is considerably lower compared to the medium resolution sensors like MERIS and MODIS. Also, the reliability of present reanalysis methods of meteorological variables seems to drop when the pixel size decreases (Luhamaa *et al*., 2011).

What could be the role of such models in forestry? Models like EST_PP could be used to produce additional yearly county and state-level estimates of timber biomass and volume increment and such model-simulated estimates could well be included into the forestry yearbooks. Another potential application of the model is producing regional 'climatological' estimates of forest productivity, i.e. when average biomass/volume increments over the certain period of years are calculated. These estimates show the potential productivity of forests in a particular geographic location and how well one or another forest (plant community) is adapted to use the temporal cycle of resources offered by local meteorological conditions. The present version of the EST_PP model is certainly a preliminary one. There are several ways to improve the existing model, especially as 1 km^2 resolution is too coarse for typical Estonian landscape. It is expected that by refining the land cover classes and pixel size, tuning the class-specific input parameters, modifying the algorithms and including additional ancillary information (soil maps, existing forestry databases) the predictive power of GPP/NPP models will improve.

There are many factors that have their influence on forest growth rate, productivity and carbon sequestration which have not been apparently considered in such simple models. However, simple models have their advantages too, since the amount of unknown parameters is limited and it is possible to avoid uncertainties introduced by additional parameters. Even if it appears that the LUE type model tests at a stand or regional and local levels fail, these models have their cognitive value and deserve serious attention. In this way, GPP/NPP models such as EST_PP provide an effective tool for quantitative analyses of how the forest productivity and carbon balance are formed and which are the most important driving environmental factors. Modern satellite-borne techniques together with the new methods of analysis of meteorological variables make it possible to carry out the analysis with acceptable spatial and temporal resolution.

At the moment, MERIS instrument on board the ENVISAT satellite has stopped working and there will be no new MERIS data. However, MODIS is still alive onboard Terra and Aqua satellites and forthcoming ESA SENTINEL-3 is planned to continue the MERIS mission. It is expected that the future satellite missions will ensure the continuity of suitable satellite images for the GPP/NPP models.

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MERIS'e GPP/NPP tulem Eesti jaoks: I. Algoritm ja mudelarvutuste esialgsed tulemused

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Kokkuvõte

Kirjeldatakse kiirguse kasutamise efektiivsuse põhimõttel töötavat Eesti maismaa taimkatte bruto-produktsiooni (GPP) ja neto-produktsiooni (NPP) mudelit EST_PP, mida rakendatakse 1 km^2 võrgustikul. Mudel tugineb MERIS'e (MEdium Resolution Imaging Spectrometer) satelliidipiltidelt määratava taimkatte poolt neelatud fotosünteetiliselt aktiivse kiirguse teguri (fAPAR) ja lehepinnaindeksi (LAI) väärtustel ja meteoroloogiliste andmete uuestianalüüsi tulemustel. Meteoandmete uuestianalüüs 11 km^2 võrgustikul on tehtud Eesti Meteoroloogia ja Hüdroloogia Instituudi (EMHI) ja Tartu Ülikooli atmosfäärifüüsikute poolt kasutades HIRLAM'i (High Resolution Limited Area Model) numbrilise ilmaennustuse mudelit. GPP/NPP mudeli rakendamiseks vajalik Eesti maakattekaart tehti DMCii (Disaster Monitoring Constellation International Imaging) SLIM-6-22 (Surrey Linear Imager – 6 kanalit – 22 m lahutus) satelliidipiltide alusel ja kasutades juba olemasolevat maakatte infot. EST_PP mudelit rakendati ajavahemikule 2003–2011. Mudelarvutuse tulemusi võrreldi MODIS'e (Moderate Resolution Imaging Spectroradiometer) GPP/NPP globaalse tulemiga Eesti ala kohta ja kaudsete NPP hinnangutega, mis tuletatud Eesti riikliku statistika andmete alusel, kasutades metsade tüvemahu juurdekasvu ja põllukultuuride saagikuse andmeid. Lisaks võrreldi mudelarvutuste tulemusi erinevates maakondades mõõdetud okas- ja lehtpuude aastarõngaste laiuste alusel tuletatud NPP hinnangutega. Üle-Eestilised NPP keskmised langesid kokku kaudsete meetoditega hinnatud NPP andmetega rahuldavalt, eriti kui arvestada mudelarvutuste suurt määramatust ja aastarõngaste mõõtmistulemuste seni veel vähest esinduslikkust. Samas pole nii EST_PP kui ka MODIS'e NPP mudelid võimelised adekvaatselt kirjeldama metsade ja põldude produktiivsuse erinevusi eri maakondade vahel ja muutlikkust aastast aastasse. Mudel vajab regionaalsete erinevuste adekvaatseks arvestamiseks kindlasti täiustamist ja kiirguse kasutamise efektiivsusel tuginev mudeli alus-põhimõte testimist. Vaatamata neile puudustele, on MODIS'e ja EST_PP mudelid heaks abivahendiks Eesti taimkatte produktiivsuse kaardistamisel ja süsiniku sidumise hinnangute tuletamisel. On head väljavaated lisada tulevikus taolised mudelarvutuse tulemused Eesti riikliku statistika igaaastastesse aruannetesse.

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