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Demonstration of large area forest volume and primary production estimation approach based on Sentinel-2 imagery and process based ecosystem modelling

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Forest biomass and carbon monitoring plays a key role in climate change mitigation. Operational large area monitoring approaches are needed to enable forestry stakeholders to meet the increasing monitoring and reporting requirements. Here we demonstrate the functionality of a cloud based approach utilizing Sentinel-2 composite imagery and process based ecosystem model to produce large area forest volume and primary production estimates. We describe the main components of the approach and implementation of the processing pipeline into the Forestry TEP cloud processing platform and produce four large area output maps: 1) Growing stock volume (GSV), 2) Gross primary productivity (GPP), 3) Net primary productivity (NPP) and 4) Stem volume increment (SVI), covering Finland and the Russian boreal forests until the Ural Mountains in 10 m spatial resolution. The accuracy of the forest structural variables evaluated in Finland reach pixel level relative Root Mean Square Error (RMSE) values comparable to earlier studies (basal area 39.4%, growing stock volume 58.5%, diameter 35.5% and height 33.5%), although most of the earlier studies have concentrated on smaller study areas. This can be considered a positive sign for the feasibility of the approach for large area primary production modelling, since forest structural variables are the main input for the process based ecosystem model used in the study. The full coverage output maps show consistent quality throughout the target area, with major regional variations clearly visible, and with noticeable fine details when zoomed into full resolution. The demonstration conducted in this study lays foundation for further development of an operational large area forest monitoring system that allows annual reporting of forest biomass and carbon balance from forest stand level to regional analyses. The system is seamlessly aligned with process based ecosystem modelling, enabling forecasting and future scenario simulation.

Keywords: forest biomass; forest carbon; Forestry TEP

Introduction

Forests and forest management are increasingly seen as important means in climate change mitigation, making biomass and carbon monitoring an essential part of forest inventories. Reliable information on forest biomass and carbon fluxes are needed to meet the reporting requirements of national and international policies and commitments like the Paris Agreement on Climate Change and the United Nations' Sustainable Development Goals (Herold et al. 2019). Forestry stakeholders need to be able to respond to the increasing demands on up-to-date forest inventory data to meet all regulatory requirements. Moreover, many forestry stakeholders choose to be involved with voluntary programmes (like forest certification schemes) that further increase the amount of required forest biomass and carbon monitoring and reporting activities.

Over the past decade, three pan-tropical, one northern hemisphere and two global forest volume and biomass products have been produced using varying combinations of field data, space borne Light Detection and Ranging (LiDAR), as well as optical and radar satellite data (Saatchi et al. 2011; Baccini et al. 2012; Thurner et al. 2014; Avitabile et al. 2016; Hu et al. 2016; Santoro et al. 2019). The products have provided a wealth of valuable information on large area forest volume and biomass monitoring from regional to global level. However, due to the varying accuracies (Rodríguez-Veiga et al. 2019), their coarse spatial resolution (at best 100 m) and temporal irregularity, their usability for forest carbon balance monitoring from local to regional level is somewhat limited. Forestry stakeholders operating in local to regional level will require information on forest standing stock and carbon sequestration on a higher spatial resolution and in regular interval to be able to respond to the increasing reporting requirements.

In this study we demonstrate the usability of an alternative approach for large area forest volume and carbon flux monitoring, using a combination of forest structural variable estimation and process based ecosystem modelling. This approach allows forest structure variable and volume estimation in high (10 m) spatial resolution, directly integrated with primary production estimation allowing carbon sequestration monitoring. Several studies have combined satellite based estimation of leaf area index with process based estimates of primary production (Running and Hunt 1993; Coops et al. 2012; Peltoniemi et al. 2015; Waring et al. 2016). While light absorption and hence gross primary production (GPP) can be adequately estimated using leaf area index, a proper estimation of both autotrophic and heterotrophic respiration requires more information on the ecosystem (Chirici et al. 2016). The novel approach of providing the additional forest ecosystem information (*e.g.* species and standing volume) through satellite images allows us to extend the use of process based models to wider areas where ground based estimates of forests are not so readily available.

Examples of widely used process based forest models suitable for regional applications include BIOME-BGC (Running and Hunt 1993; White et al. 2020) and 3-PG (Landsberg et al. 1997; Coops et al. 2012). PREBAS (Valentine and Mäkelä 2005; Minunno et al. 2019) is a more recent model sharing the same basic approach, with special emphasis on the realism of tree structure (Mäkelä and Valentine 2020). The regional applicability of PREBAS has been demonstrated particularly for boreal forests using ground-based wall-to-wall data on forestry variables (Holmberg et al. 2019; Mäkelä et al. 2020; Forsius et al. 2021).

Process models also enable future projections of the state of the forest, provided that sufficiently detailed inputs of current forest structure and model drivers, such as climate and management, are available. Such dynamic approach has two main advantages over the static mapping of forest biomass: 1) it allows spatially explicit identification of areas of carbon sinks and sources and 2) it allows forecasting of future carbon sequestration in forest ecosystems, based on different scenarios (e.g. changes in management or climate). Overall, this approach combines estimation of current forest characteristics seamlessly with carbon flux modelling for annual carbon sequestration estimation and future forecasting.

The process based approach is particularly suitable for boreal and temperate forests, with ample field datasets and a long tradition in Earth Observation based estimation of the required forest structural input variables. Satellite based methods for large area estimation of forest structural variables in 10-30 m resolution have been developed since the 1990’s (Tomppo 1991; Tokola et al. 1996; Häme et al. 2001), and are still in operational use together with new data sources like LiDAR (Kangas et al. 2018). Datasets are compared and new approaches are continuously tested to improve estimation accuracies. Studies have reached pixel level Root Mean Square Error (RMSE) of 30-60% of the mean for the key forest structure variable (incl. basal area, diameter, height and volume) using both optical and radar data including e.g. Sentinel-2, Landsat-8 data and AP data (see e.g. Häme et al. 2013; Antropov et al. 2017; Sirro et al. 2018; Astola et al. 2019; Sánchez-Ruiz et al. 2019; Santoro et al. 2019b).

New cloud based processing environments allow implementation of Earth Observation based forest monitoring approaches for large area monitoring, taking advantage of massive quantities of satellite imagery. The Forestry Thematic Exploitation Platform (Forestry TEP; https://f-tep.com/) is designed to facilitate cloud based utilization of Earth Observation and other data in support of forest monitoring. Processing algorithms for any task can be created and implemented, utilizing the datasets available in one of the Copernicus Data and Information Access Services

(DIAS) platforms, or uploaded to the platform by the user. Cloud based processing platforms like Forestry TEP allow implementation of large area production forest carbon monitoring products in an operational manner.

The objective of this study is to demonstrate the functionality of a cloud based processing approach utilizing Sentinel-2 imagery, field data and a process based ecosystem model to produce large area forest volume and primary production estimates. We aim to reach this objective by:

1. Designing a processing routine for forest variable and primary production estimation combining field data, satellite imagery mosaic and a process based ecosystem model.
2. Implementing the routine as a processing pipeline into the Forestry TEP cloud processing platform to allow effective large area forest estimation.
3. Executing the processing pipeline to produce four large area output maps: 1) Growing stock volume (GSV), 2) Gross primary productivity (GPP), 3) Net primary productivity (NPP) and 4) Stem volume increment (SVI), covering Finland and the Russian boreal forests until the Ural Mountains in 10 m spatial resolution.

The approach demonstrated in this study allows regional level monitoring with region specific models to derive consistent forest variable and carbon flux estimates in high spatial resolution.

Materials and methods

Sentinel-2 multitemporal image mosaic

With two satellites in orbit, the European Space Agency (ESA) Sentinel-2 mission provides five days imaging frequency at the equator and 2-3 days imaging frequency at mid-latitudes. The Multi-Spectral Instrument (MSI) on board Sentinel-2 satellites has 13 spectral bands with 10 m (four bands), 20 m (six bands) and 60 m (three bands) spatial resolutions. The Level 2A surface reflectance product is systematically generated by ESA and distributed in tiles of 100 x 100 km^2.

In this study, a mosaic of Sentinel-2 Level 2A composite images was created, covering Finland and the western part of Russian taiga until the Ural Mountains (Figure 1). The mosaic was constructed creating cloud-free composite images for the 214 Sentinel-2 tiles that form the target area. For each tile, imagery from the 15th June to 31st August 2019 and from the 15th June to 31st July 2020 were used.

<Insert Figure 1 here.>

The compositing process can be roughly divided into three steps: data selection, merging algorithm and quality control. For the composite images calculated in this study, all images with less than 20% cloud cover were used. The number of images used varied between four and 15 per tile. The slight majority of the images were from year 2020. The average proportion of 2020 observations used in the 214 tiles was 55% and median 59%.The figures were computed by dividing the number of 2020 observations by the total number of observations for each tile (giving tile-wise proportions of 2020 imagery) and subsequently computing the average and median of these values over the entire mosaic.

The objective of the compositing process is to create a cloud-free image out of many observations, which are imperfect (*e.g.* that include clouds, haze or smoke). To do this, each pixel is evaluated according to four criteria: cloudiness, resemblance to usual pixels observed in the location (based on a reference mosaic), haze and shadows. A weight is then given for each pixel according to the four criteria. These weights are used to average the observations given as input and produce the final image. The weighted average merging algorithm is defined mathematically as follows. Let $X=(x_1, x_2,\dots,x_t)$ denote a time series of observations for a given geographical point, where each element x_i denotes an observation from the Sentinel-2 satellite. Each observation $x=(x(0), x(1),\dots,x(12))$ consists of the band values $x(0), x(1),\dots,x(12)$, where $x(0)$ is the value of the scene classification band provided with the Sentinel-2 Level 2A product and $x(1),\dots,x(12)$ correspond to the values of the Sentinel-2 bands 1, 2, 3, 4, 5, 6, 7, 8, 8a, 9, 11 and 12, respectively.

The weight of observation x is given by the formula $w(x)=m_{\mathrm{c}}(x)\, m_{\mathrm{d}}(x)\, m_{\mathrm{h}}(x)\, m_{\mathrm{s}}(x)$, where $m_{\mathrm{c}}(x)$,$m_{\mathrm{d}}(x)$,$m_{\mathrm{h}}(x)$ and $m_{\mathrm{s}}(x)$ represent multiplier functions that are based on scene classification, spectral distance, haze and shadows, respectively. Each multiplier function produces a value between 0 and 1 that describes the validity of the observation with respect to one of the criteria. For example, if the multiplier function m_{h} gives the value 1, it means that the observation is assumed to be totally valid with respect to haze, that is, haze-free. If the weight of an observation is close to one, it means that the validity of the observation is high with respect to all of the criteria.

The scene classification multiplier is defined by the formula:

$$m_{\mathrm{c}}(x) = \begin{cases} 1 \; if \; x_0 \in V \\ 0 \; otherwise \end{cases}, \qquad (1)$$

where $V = \{2,4,5,6,7\}$ denotes the set of valid classes for the scene classification band (2: dark area pixels, 4: vegetation, 5: not vegetated, 6: water, 7: unclassified).

The spectral distance multiplier is used to evaluate the resemblance of the pixel to cloud free pixels observed in the location, and is defined using the formula:

$$m_{\mathrm{d}}(x) = \left(\min\left(\max\left(1 - \frac{d(x,L)}{d_{\max}}, 0\right), 1\right)\right)^{p_{\mathrm{d}}}, \qquad (2)$$

where $L=\{l_1,\ldots,l_n\}$ is a collection of n cloud-free reference observations and $d(x,L)$ denotes the minimum spectral distance between observation x and the observations in L, that is, $d(x,L)=min\{d_e(x,l) \mid l \in L\}$, where d_e represents the Euclidean distance function. d_{max} and p_d are constants whose values are set to 3000 and 6, respectively. The values were set through visual evaluation of preliminary test results for one tile in Finland (35VLJ) and earlier experience, aiming to maximize the number of observations without including any noticeable haze in the final product.

The haze multiplier is defined using the formula:

$$m_{\mathrm{h}}(x) = \left(\min\left(\max\left(1 - \frac{x_1}{h_{\max}}, 0\right), 1\right)\right)^{p_{\mathrm{h}}}, \tag{3}$$

where x_1 represents the value of the Sentinel-2 band 1, $h_{max} = 3000$ and $p_h = 6$.

The shadow multiplier is defined by the formula:

$$m_{\mathrm{s}}(x) = \begin{cases} \min\left(max\left(1 - \frac{x_s - c_0}{c_1 - c_0}, 0\right), 1\right) & if\ x_s \leq c_1, \\ \min\left(max\left(1 - \frac{x_s - c_1}{c_2 - c_1}, 0\right), 1\right) & otherwise \end{cases}, \tag{4}$$

where x_s is the value of the Sentinel-2 band 8 (near infrared), $c_0 = 100$, $c_1 = 250$ and $c_2 = 2000$.

Finally, given the time series of observations $X=(x_1,x_2,\ldots,x_t)$ and the corresponding weights $w(x_1),w(x_2),\ldots,w(x_t)$, the weighted average a_X of the observations is given by the formula:

$$a_X = \frac{\sum_{i=1}^{t} x_i w(x_i)}{\sum_{i=1}^{t} w(x_i)} \tag{5}$$

In this study, only seven spectral bands were output into the resulting composite images (Table 1). These included the six bands to be used in the forest structural variable estimation (see below) and the blue band to enable real colour visualization of the composite images. In addition to the seven spectral bands, a quality parameter was calculated. The quality band value described the probability of at least one good observation, which was calculated per pixel using the formula $P = 1 - \prod(1-p_i)$, where p_i denotes the probability that observation i was good for $i \in \{1,...,n\}$, where n denotes the number of observations for the pixel. For the final composite images, all bands were resampled to match the 10 m resolution bands (four out of seven bands used; Table 1) using nearest neighbour resampling.

<Insert Table 1 here.>

Field data

Field plot measurements were used as 1) training data for the forest variable model creation and 2) reference data for the uncertainty assessment. The field data plots had been measured by the Finnish Forest Centre (https://www.metsakeskus.fi/node/321) in 2019 and spread over six Sentinel-2 tiles (Figure 2). Three different plot radii had been used in the measurements: 9 m in young and advanced managed forests with a relatively high tree density; 12.62 m in forest with a low stem density but usually high volume due to the mature development stage and 5.64 m in seedling stands. Since the mosaic included Sentinel-2 data from summers 2019 and 2020, all plots were visually screened for recent clearcuts and plots that had been measured before the harvesting were removed. At the same time, all plots that were located in areas with atmospheric disturbance were removed. Around two thirds of the plots were used for model training, while the remaining one third was used for the uncertainty assessment. The plots used for uncertainty assessment were selected by choosing every third plot of the original field plot database before visual screening of the plots. At the end, 5226 field plots were used, 3471 for the creation of the model and 1755 for the uncertainty assessment.

<Insert Figure 2 here.>

Eight variables were produced with the forest structural variable models, including seven intermediate variables needed as input for process based ecosystem modelling, and one output variable (Table 2). The basal area (G), diameter at breast height (D), height (H), growing stock volume (GSV) and site type were available from the field dataset measured by the Finnish Forest Centre. The growing stock volume had been derived using tree-wise allometric equations. In addition to the total aggregate basal area, the dataset provided basal areas for pine, spruce and broadleaf trees for each plot. This information was used to derive the species proportions used as input for the modelling. During the model creation phase, all of the eight variables were treated as continuous variables. In the case of the site type, average percentage of each site type class was calculated for each cluster (see Forest Structural Variable Estimation section) and thereby estimated to each pixel at the estimation phase. Subsequently, the site type with the highest percentage was chosen for the pixel. A standard Finnish site type classification based on the fertility of the site type (defined based on the ground vegetation) was used (Table 3). The full classification scheme includes eight classes, arranged according to decreasing fertility. In the field datasets used in the study, only six classes were present. For this reason, only the six classes are included in the results.

<Insert Table 2 and Table 3 here.>

Weather data

Weather inputs were needed in the primary production estimation. Weather information was extracted from Climate change web picker (Clipick, http://home.isa.utl.pt/~joaopalma/projects/agforward/clipick/) and National Centers for

Environmental Prediction (NCEP) Climate Forecast System (Version 2, CFSv2, https://rda.ucar.edu/datasets/ds094.1/#!description) datasets. These two high resolution climate datasets provided daily meteorological simulations as weather inputs for PREBAS (see below), including the Photosynthetic Photon Flux Density (PPFD; mol/m^2/d) above the canopy, air temperature (°C), Vapor-Pressure Deficit (VPD; kPa) and precipitation (mm/d), for the tiles from 2019 to 2020.

Forest structural variable estimation

The Probability forest classification and estimation approach (Häme et al. 2001) was used to derive the forest structural variable estimates that served as input for the process based ecosystem model. The classification and estimation approach includes three modules: 1) Proba Cluster, 2) Proba Model and 3) Proba Estimates. The overall workflow of the forest structural variable estimation is illustrated in Figure 3. The process was started with Proba Cluster module, performing image clustering of the input images with maximum likelihood clustering into 60 clusters using six bands from the mosaic (B03 Green, B04 Red, B05 Red Edge 1, B08 NIR, B11 SWIR 1.6 µm and B12 SWIR 2.1 µm). These six bands were chosen based on earlier experience (Astola et al. 2019) and the decision to avoid the blue band due to its sensitivity to any remnant atmospheric effects in the composite images. After the clustering, the Proba Model module was used to associate the field measurements with the clusters. Both spectral statistics and forest variable values are needed for each of the 60 clusters to perform the final pixel-wise forest structure variable estimation in the Proba Estimates module. The forest variable values for each cluster were computed as an arithmetic mean or median of all the field measurements belonging to this cluster.

Based on earlier experience (Häme et al. 2001; Sirro et al. 2018), median value was used to derive cluster values for basal area (G), diameter (D), height (H) and growing stock volume (GSV), while mean value of the sample plots falling into a given cluster was used for the rest of the variables. The median approach is less affected by potential outlier plots, but the average approach produces more reasonable estimates for the proportional variables (i.e. their sum equals closer to 100).

<Insert Figure 3 here.>

The resulting model was analysed by comparing visually the cluster values, the cluster distribution and the original satellite imagery. This visual verification and modification phase allowed fine tuning of the model to remove peculiarities caused *e.g.* by single field plots fallen into a cluster. Clusters that mainly covered non-forest areas were set to null values at this point, even though some field plots might have fallen into them. At this point, both the spectral statistics as well as the forest structural variable values were known for each of the 60 clusters.

Finally, the Proba Estimates was used to compute a forest-variable estimate for each image pixel. A multivariate normal distribution for each cluster was characterized using its mean vector and covariance matrix. A cluster membership probability for a spectral vector x was computed for five spectrally closest clusters and these probabilities were scaled to sum up to 1. These cluster membership probabilities were used as weights when deriving a final estimate for a given pixel as a weighted sum of reference data values for five spectrally closest clusters (Häme et al., 2001).

$$f(x) = \sum_{c=1}^{N} P(c|x)\, f_c \qquad (6)$$

where $f(x)$ is the target variable value for spectral vector x, $P(c|x)$ the probability for spectral vector x belonging to cluster c, f_c the target variable value for cluster c and N the number of clusters.

Note that also the site type was treated as continuous variable at this point, since it was calculated as percentages of site types in each cluster (based on the number of plots fallen into the cluster). The site type was subsequently converted into a category variable by choosing the site type class with the highest percentage as the site type for a given pixel. All of the processing was run in the Forestry TEP online environment.

Process based ecosystem modelling

PREBAS is a semi-empirical forest growth simulator (Mäkelä 1997; Valentine and Mäkelä 2005; Peltoniemi et al. 2015; Minunno et al. 2019), to estimate forest carbon and water fluxes and current biomass and dimensional growth of even-aged forest stands. PREBAS consists of a daily-time-step module (PRELES) to estimate photosynthesis, soil moisture and evapotranspiration, and an annual-time-step module (CROBAS) to allocate the assimilated carbon to respiration and structural growth of biomass components. Intended for large-scale applications in forestry, the model has modest input requirements (Table 4) and feasible runtimes. Parameterized with Bayesian calibration for three boreal species, the model has been demonstrated to perform adequately in country-wide applications (Minunno et al 2019; Holmberg et al. 2019; Minunno et al 2016).

<Insert Table 4 here.>

PRELES (PREdict Light-use efficiency, Evapotranspiration and Soil water) estimates photosynthesis or gross primary production (GPP) and evapotranspiration using a light-use-efficiency (LUE) approach linked to soil moisture. PRELES was developed so as to run with standard weather data (Peltoniemi et al. 2015). It calculates photosynthesis using potential LUE and multiplicative modifying factors that depend on the environmental drivers. One of these is soil moisture, which is estimated in PRELES using a simple bucket model that takes precipitation as input and is depleted by evapotranspiration. Evapotranspiration is divided into transpiration by the canopy and evaporation from surfaces and ground (including the ground layer). A similar modelling approach is used as in photosynthesis, where modifying factors reduce the potential evapotranspiration. Transpiration also strongly depends on photosynthesis due to their link through stomatal control. PRELES therefore shows strong interlinkages between photosynthesis, evapotranspiration and soil water (Tian et al. 2020).

CROBAS is an individual tree growth model that can be applied in different stand configurations, climates and sites. Stand configurations are derived from the structural forest variables, and the weather effects are incorporated through impacts on photosynthesis, respiration and tissue longevity. In this study, we use the climate-dependent potential photosynthetic production of a stand, quantified by PRELES, to derive the geographic variation of the other relevant metabolic parameters, following the procedure proposed by Mäkelä et al. (2016). Edaphic site characteristics are described in terms of an aggregated soil fertility parameter that regulates below-ground allocation of carbon. Soil fertility parameter with six categories was used, relating to herb-rich, herb-rich heath, mesic heath, sub-xeric heath, xeric heath and barren heath forests, in accordance with the Finnish site classification system (Cajander 1949; Table 3).

Total tree growth in CROBAS equals annual net photosynthetic production. Respiration is divided into growth and maintenance components, where maintenance is assumed proportional to live biomass and growth respiration is a proportion of growth. Total growth is allocated annually to the biomass components that comprise foliage, fine roots and three sapwood fractions, stems, branches and coarse roots. Carbon allocation between wood and foliage is based on the pipe model (Shinozaki et al. 1964) with dynamic crown rise, and allocation between fine roots and foliage assumes that fine-root to foliage ratio depends on nutrient availability, quantified in terms of site type (Valentine et al. 2013).

Uncertainty assessment

The uncertainty assessment was based on the reference dataset of field plot measurements described above. The reference field measurements were available only from Finland. For continuous forest variables (*i.e.* all but site type), Root Mean Square Error (RMSE) and bias of the estimates were calculated as:

$$RMSE = \sqrt{\frac{\sum_i (y_i - \hat{y}_i)^2}{n}} \tag{7}$$

$$BIAS = \frac{\sum_i (y_i - \hat{y}_i)}{n} \tag{8}$$

where y represents the reference values, $\hat{y}$ represents the estimated values and n is the number of samples. Both of these values were also compared to the mean value of the variable in the uncertainty assessment field samples, deriving relative metrics, denoted as RMSE% and BIAS%.

For site type uncertainty assessment, confusion matrix was used. From this matrix, proportions of correctly classified samples and distribution of errors between classes were analysed and overall accuracies were calculated.

For the Russian part of the output products, visual evaluation of the maps was performed. The output maps were visually compared to the underlying satellite images. In addition, Google Earth very high resolution imagery was used to check any areas were potential errors were detected. Regardless of the lack of field reference data for the Russian part, the inclusion of the area was considered important to test and demonstrate the technical feasibility of the processing pipeline developed in this study for large area forest monitoring. Visual evaluation of the products allowed evaluation of the consistency of the results throughout the area of interest, noting potential effects of atmospheric disturbance left in the composite images and effects the different weather datasets used in the study. No quantitative reference data was available to evaluate the uncertainty of the primary production variables. Please see the discussion section for further thoughts on the potential and necessity to evaluate the level of uncertainty of the primary production output layers.

Forestry TEP processing pipeline

The main objective of this study was to demonstrate the functionality of a cloud based processing pipeline to produce 1) Growing stock volume (GSV), 2) Gross primary productivity (GPP), 3) Net primary productivity (NPP) and 4) Stem volume increment (SVI) maps in 10 m spatial resolution for the target area. To enable the processing of the 214 Sentinel-2 tiles for the production of the output layers, a semi-automated processing pipeline was developed and implemented in Forestry TEP platform.

In total, seven individual processing services were used in the processing pipeline (Table 5). The pipeline was divided into three sections: 1) Model creation, 2) Model verification and 3) Operational production (Figure 4). While the 'Model creation' and 'Operational production' parts of the processing pipeline were run in an automated fashion, the ‘Model verification’ part involved visual analysis steps that enabled fine-tuning forest structural variable models to reach optimal results (as described above).

<Insert Table 5 amd Figure 4 here.>

In the demonstration conducted in this study, the ‘Model creation’ part of the pipeline was started by executing the ProbaCluster service with six input Sentinel-2 tiles where reference data was available, performing maximum likelihood clustering for the images. Note that only one clustering was performed, containing all of the six tiles together as the input. This was followed by execution of the ProbaModel service with the ProbaCluster output and 3471 field sample plots as input data. The ProbaModel service calculated forest variable values for each cluster as an arithmetic mean or median of all the field measurements belonging to a given cluster. Thereby, the ‘Model creation’-part of the processing pipeline resulted in two models, one for the median variables and one for the average variables. These two models were analyzed in the ‘Model verification’ part of the pipeline, followed by ProbaEstimates test runs. The ProbaEstimates test runs for the six Sentinel-2 tiles produced forest variable estimates for each image pixel as the weighted average of the five spectrally closest clusters, the weight being the probability of the pixel belonging to the cluster (Häme et al. 2001). This allowed uncertainty assessment of the model outputs using the 1755 uncertainty assessment plots. The ‘Model creation’ and ‘Model verification’ phases were executed using the graphical user interface (GUI) of the Forestry TEP. For further details of the Probability forest variable estimation chain, please refer to the ‘Forest structural variable estimation’-section above.

At this point, all the necessary datasets and components were ready for the demonstration of the full scale processing, i.e. the creation of the output products. The output layers of the demonstration were produced in the ‘Operational production’ part of the processing pipeline (Figure 4). All the 214 tiles of the Sentinel-2 mosaic were processed, creating the full coverage maps. The first part of the operational production consisted of creation of the masks with the ThresholdMasking service and production of the forest structural variable layers for all tiles with the ProbaEstimates service. The ThresholdMasking service utilized only the Sentinel-2 composite images as input. ‘No data’ areas, which were mainly remnant clouds, were masked out based on the mosaic image quality band, using a visually defined threshold value of 4000 (quality range 0-10000). Values lower than 4000 were masked out as ‘No data’ (mask value 1). Water areas were masked out based on the Near Infrared (NIR) band (band 5 in the mosaic tiles). Pixels with NIR value less than 800 (8% reflectance) were masked out as ‘Water’ (mask value 2). All other values were flagged as valid data at this point (mask value 0).

Subsequently, the ProbaEstimates service was run for the Sentinel-2 tiles using the final forest structural variable model, followed by the CategoryProbabilities2Category service, which created one single site type layer from the probabilities of each site type class. At this point, the output files of both the ProbaEstimates as well as the CategoryProbabilities2Category went into the ProductPostProcessing service, which performed masking of the forest structural variable outputs, separated the variables into different layers and created colored images for easy visual evaluation of the results. At this point also all pixels with zero basal area were masked as ‘Non-tree cover’.

Apart from the growing stock volume (GSV) layer, which itself was an output layer, all forest structural variable layers were used as input layers for the primary production component of the processing pipeline. The primary production layers were created with the PrimaryProduction service which conducted the PREBAS modelling utilizing the forest structural values and weather data as inputs. For description of the PREBAS model, please refer to the ‘Process based ecosystem modelling’-section above. The ‘Operational production’ part of the pipeline was run through the Representational State Transfer Application Programming Interface (REST API). This allowed chaining of subsequent pipeline components into an automated processing chain, allowing bulk processing of the 214 Sentinel-2 tiles and demonstrating operational functionality of the forest carbon processing approach.

Results

The uncertainty assessment results are provided in Table 6 and Table 7. The three key input variables for the PREBAS model are the basal area (G), diameter (D) and height (H). For all these variables, the relative RMSE remains below 40%. The growing stock volume (GSV) is an output map variable as such. The relative RMSE is rather high (59%), but it has to be remembered that this is on pixel level. Errors tend to balance out over larger areas. The GSV bias (-5.6%) indicates slight overall underestimation of the values. This is expected to be caused primarily by underestimation of GSV in high volume forests. For the other variables, the biases are very small, indicating high quality of estimates for large areas.

<Insert Table 6 here.>

For the site type, the overall accuracy is 62%. It must be noted however, that the majority of the erroneous estimations are off by only one class. Only 3.3% of the uncertainty assessment reference plots (58 out of 1755) were off by more than one class. Remembering that the site type classes are ordered by decreasing fertility, this indicates that the effects of the erroneous estimations have minor effect in the primary production estimates.

<Insert Table 7 here.>

The specifications of the output products are described in Table 8. All of the products were output in 214 GeoTiff format tiles, matching the size and location of the original Sentinel-2 tiles. The units used in the various products were standard units generally used with the variables. The products also included values for masked out areas (more specifically for Non-tree cover, Water and Clouds or other no data), which were consistent throughout the products.

<Insert Table 8 here.>

Qualitatively the output products were of high quality, showing no clear systematic artefacts or errors. All of the output maps can be viewed in full detail at http://polarcode.vtt.fi/assesscarbon/. Particularly the growing stock volume (GSV) product (Figure 5) showed consistent quality over the entire target area, with major regional variations in level of volume clearly visible, and with noticeable fine details when zoomed into full resolution. This type of product provides valuable information for regional level monitoring, due to the consistent methodology applied throughout the region, resulting in comparable results in different parts of the region. At the same time, due to its high spatial resolution, the maps allow practical forest management monitoring down to forest stand level. The volumes reached over 300 m^3/ha at some points of the map, but generally the high volume forest stands suffered from underestimation of volume. This is an inherent problem in the estimation model, which uses the average of the five nearest clusters while defining the pixel values.

<Insert Figure 5 here.>

In general, the primary production variable output maps (Figure 6) showed similarly high quality and fine detail. The only clear artefact was the border between the two weather datasets used. This was mainly caused by the differences in the two weather datasets used in the study. Please see more discussion on the topic in the discussion section. The values for gross primary production (GPP) range between 0 and 40 CO_2t/ha/a, and the net primary production (NPP) between 0 and 20 CO_2t/ha/a. These are both reasonable values for boreal forests. The Stem volume increment (SVI) reaches up to 13 m^3/ha/a, which may indicate some overestimation in some parts of the map, although such values may be possible in the southern part of the target area.

<Insert Figure 6 here.>

Discussion

In this study we have demonstrated the functionality of a cloud based processing approach utilizing Sentinel-2 imagery and a process based ecosystem model to produce forest volume and primary production estimates for large geographical areas in 10 m spatial resolution. These data can be used to derive estimates on forest biomass and carbon fluxes from forest stand level to regional analyses. Such information is required to meet monitoring and reporting requirements of an increasing number of legislative and voluntary obligations that forestry stakeholders nowadays have. Furthermore, the inclusion of the process based forest ecosystem model into the system implies that the approach can be used as a basis for future forecasting under various scenarios with changing forest management options and climate scenarios.

Most previous studies estimating forest primary production with satellite data have utilized NDVI based indicators (Coops et al. 2012; Chirici et al. 2016; Running et al. 2004) that allow estimation of total, not tree-specific leaf area. Although valuable for estimating total carbon fluxes, total leaf area may be less relevant in the forestry context especially in areas where canopy coverage is low, such as in the temperature limited boreal and water limited arid regions. In line with this, model studies using ground based data have given indication that NDVI based algorithms tends to overestimate

GPP in northern latitudes (Peltoniemi et al. 2015). In this study, we derived forest biomass and leaf area from forest structure variables instead of NDVI, using existing tree structure models embedded in the ecosystem model PREBAS. This allowed us to make a distinction between trees and ground vegetation that have different roles in ecosystem respiration and hence NPP and volume growth. The forest structural variables were also essential for determining both autotrophic respiration and growth allocation.

The reliability of the integrated system for the estimation of primary production developed here depends on the goodness of the forest structural variables input into the forest model and the robustness of the model itself. Errors in the initial state forest variables will propagate through model predictions and, at the same time, weaknesses in model structure would affect model performances. The levels of uncertainty reached in this study for the forest structural variables indicate suitability of the approach for large area monitoring. The continuous forest structural variable accuracies of the model developed in this study were on the same level that has been achieved in previous studies for forest variable estimation with varying datasets and methods (Häme et al. 2013; Sirro et al. 2018; Astola et al. 2019). However, these studies have been conducted in smaller study areas with single data images, whereas in this study, a single model was created using field data covering the range from south to north boreal zone, and the analysis was based on composite images. Large variation of forest types within the study area complicates forest structural variable estimation. Furthermore, composite images tend to have more artificial variation in reflectance levels than single day images. Considering these complications, the results obtained in this study can be considered promising for operational application of the demonstrated forest biomass and carbon monitoring approach.

For the site type estimation, the 62% overall accuracy obtained in this study is significantly lower than the 70-95% OA's typically achieved for categorical variables (Häme et al. 2013; Sirro et al. 2018) with the Probability approach. It must be noted however, that categorical variables often include fewer classes (e.g. only forest vs. non-forest), while in this study six fertility classes were used. The majority of the erroneous estimations were off by only one class, having a minor effect on the primary production estimation. Nevertheless, the high uncertainty in site type mapping witnessed in this study highlights the need for further improvement in site fertility mapping, as information on fertility is among the key inputs for primary production estimation. Not only the systems for site fertility vary between countries, the information is typically not available in high resolution and is difficult to map through remote sensing. Enhanced approaches for deriving fertility information in 10 m spatial resolution in a standardized manner over large areas would have the potential to greatly improve high resolution primary production modelling.

It has to be remembered also that the quantitative uncertainty evaluation of the forest structural variables applied to the Finnish portion of the maps only. Although the boreal forest ecosystems are similar throughout the study area, the forest management approaches vary significantly between Finland and Russia. This affects forest structure, and thereby the forest structural variables. It would therefore be important to have field data available throughout the area of interest. Overall, setting up a comprehensive and transparent uncertainty evaluation procedure is crucial for operational application of the type of mapping and monitoring approach demonstrated in this study.

While this study has demonstrated that combining satellite data with a process based forest ecosystem model is technically feasible over fairly large areas, the primary production estimates still need to be carefully evaluated against ground based forest growth measurements and other available data, such as variables monitored in flux towers. Although process based models have been shown to provide accurate estimates of primary production variables in the boreal zone and the GPP estimates reported in this study are consistent with eddy-covariance based measurements for the Boreal forests (Minunno et al. 2016, 2019), it would be important to define uncertainty evaluation procedures for the combined use of satellite based forest structure input data and process based ecosystem models. PREBAS was developed and calibrated for forest commercial species in Finland, i.e. Scots pine, Norway spruce and Silver birch (Minunno et al. 2016: 2019). The model has shown robust performances in predicting forest growth and primary production of managed forests at landscape (Holmberg et al. 2021) and country level (Holmberg et al. 2019). However, the model reliability should be better tested for forest ecosystem characterized by more complex structure such us uneven aged mixed stands. For those type of ecosystems an accurate evaluation of the integrated system developed here is desirable. In the future, a data assimilation approach could be used to fuse multiple source of information (i.e. model predictions, satellite based estimates, field measurements) accounting for their relative uncertainty.

The main bottleneck for the processing pipeline implemented in the Forestry TEP platform turned out to be the weather data that is needed in the primary production modelling. As the primary data source (Clipick) did not cover the entire interest area, a secondary data source (NCEP) was required for the easternmost part of the area. However, the secondary data source had a very slow machine interface taking up to 10 min to get data values. Furthermore, each input weather variable needed to be fetched separately from NCEP and the variables had different grid sizes. All this forced us to use a 100 x 100 km grid for the NCEP, while 20 x 20 km grid was used for the primary Clipick database. Finally, differences were noticed, particularly in precipitation and CO_2

values between the two datasets. These differences, together with the different grid size, are believed explain the visible border in the primary production results between the two datasets. Systematic solutions to handle such discrepancies between weather datasets need to be defined and the most appropriate weather data sources need to be found, in order to be able to provide consistent high quality outputs in any target areas globally.

In theory, the coarse spatial resolution of the weather input data could be seen as a limiting factor for forest primary production modelling in 10 m spatial resolution. The effects of local variations in weather (e.g. due to vegetation, hydrology and elevation) are not captured in these datasets. However, small scale variation of weather inputs do not have a significant impact on primary production predictions, because PREBAS is more sensitive to forest structural variables than to weather inputs (Minunno et al. 2016; Mäkelä et al. 2020).

Conclusion

The demonstration conducted in this study lays a foundation for an operational large area forest growing stock and carbon sequestration monitoring system that allows annual reporting of forest biomass and carbon balance from forest stand level to regional analyses. The products could be used to support forestry stakeholders to meet the requirements of the increasing amount of forest carbon related reporting e.g. for forest certification, carbon markets and consumer demands. Due to their high spatial resolution, the products would also allow efficient precision forest management, minimizing the need for field work and optimizing forest management planning. Furthermore, the system is seamlessly aligned with process based ecosystem modelling allowing forecasting and future scenario simulation. Further work is still needed to improve and verify several aspects of the system, as discussed above. Overall the envisioned system aims to respond to forest biomass and carbon monitoring requirements for a wide range of stakeholders from private forest owners and forestry companies to non-government organizations, government departments and intergovernmental organizations, providing them with means to respond to the increasing forest monitoring requirements in an efficient manner.

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Data Availability Statement

The output layers of the study can be viewed at: http://polarcode.vtt.fi/assesscarbon/

Declaration of interest statement

The authors declare no conflict of interest.

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Table 1. Spectral bands available in the composite images.

Sentinel-2 band	**B02**	**B03**	**B04**	**B05**	**B08**	**B11**	**B12**
Wavelength	Blue 0.49 µm	Green 0.56 µm	Red 0.67 µm	Red Edge 1 0.71 µm	NIR 0.84 µm	SWIR 1.61 µm	SWIR 2.19 µm
Original spatial resolution	10 m	10 m	10m	20 m	10 m	20 m	20 m

Table 2. Variables produced during the processing, including both intermediate and output variables. Abbreviation and units provided in parenthesis. Final output variables in Italics.

Forest structural variable model	**Primary production model**
Basal area (G; m^2/ha)	*Gross primary productivity (GPP; CO_2t/ha/a)*
Diameter at breast height (D; cm)	*Net primary productivity (NPP; CO_2t/ha/a)*
Height (H; m)	*Stem volume increment (SVI;* m^3/ha/a*)*
Pine proportion (P%; % of G)	
Spruce proportion (Sp%; % of G)	
Broadleaf proportion (Bl%; % of G)	
Site type (Site; Finnish site types, Table 3))	
Growing stock volume (GSV; m^3/ha*)*	

Table 3. Finnish site type classification used to describe fertility level.

Site type code	**Finnish name**	**English translation**
Site-1	Lehto	Herb-rich forest
Site-2	Lehtomainen kangas	Herb-rich heath forest
Site-3	Tuore kangas	Mesic heath forest
Site-4	Kuivahko kangas	Sub-xeric heath forest
Site-5	Kuiva kangas	Xeric heath forest
Site-6	Karukkokangas	Barren heath forest
Site-7	Kalliomaa ja hietikko	Rock and sand outcrops
Site-8	Lakimetsä ja tunturi	Mountain heaths

Table 4. Input variables required to run the PREBAS model implemented in this study.

Variable	Abbreviation	Units	Source
Basal area	G	m^2/ha	Structural forest variable estimation
Diameter at breast height	D	cm	
Height	H	m	
Species proportions (Pine, Spruce, Broadleaf)	P%, Sp%, Bl%	% of G	
Site fertility type	Site	See Table 3	
Photosynthetic Photon Flux Density	PPFD	mol m^{-2}/d	Clipick/NCEP
Mean daily air temperature	T	°C	
Vapor-Pressure Deficit	VPD	kPa	
Precipitation	P	mm/d	

Table 5. Forestry TEP service components used in the processing pipeline.

Name	**Description**
ProbaCluster	Performed unsupervised image clustering with maximum likelihood clustering into 60 clusters.
ProbaModel	Calculated forest variable values for each cluster as an arithmetic mean or median of all the field measurements belonging to a given cluster.
ProbaEstimates	Computed estimates of forest variables for image pixels as the weighted average of the five spectrally closest clusters to any given pixel, the weight being the probability of the pixel belonging to the cluster (Häme et al. 2001).
ThresholdMasking	Created masks for an input image by thresholding the Sentinel-2 composite images (see more details in the text)
CategoryProbabilities2Category	Converted multiple layers of site type class probabilities (each of which were outputs from ProbaEstimates for a given site type probability) into one single site type layer by choosing the highest probability site type for each pixel.
ProductPostProcessing	Created masked end-products from ProbaEstimates outputs using the masks created by the ThresholdMasking (see above).
PrimaryProduction	Calculated selected primary production variables with the PREBAS model (see more details in the 'Process based ecosystem modelling'-section).

Table 6. Uncertainty metrics for continuous variables. Units of the variables given in parenthesis. RMSE% refers to the RMSE value as a proportion of the mean value of the variable.

Metric	**G**	**GSV**	**D**	**H**	**PINE %**	**SPRUCE %**	**BL %**
	(m^2/ha)	**(m^3/ha)**	**(cm)**	**(m)**	**(% of G)**	**(% of G)**	**(% of G)**
RMSE	7.18	84.49	5.73	4.57	29.3	26.7	20.3
RMSE %	39.4	58.5	35.5	33.5	64.1	89.6	90.7
Bias	-0.65	-8.01	-0.15	0.00	0.7	-0.7	-0.4
Bias %	-3.6	-5.6	-0.9	0.0	1.6	-2.5	-1.8

Table 7. Confusion matrix for the site type variable.

				Est.				
		Site-1	**Site-2**	**Site-3**	**Site-4**	**Site-5**	**Site-6**	**Total**	**User Acc.**
	Site-1	0	7	20	0	0	0	27	0.0
	Site-2	0	15	209	7	0	0	231	6.5
	Site-3	0	20	917	77	0	0	1014	90.4
	Site-4	0	0	269	151	0	0	420	36.0
Ref.	**Site-5**	0	0	29	32	0	0	61	0.0
	Site-6	0	0	1	1	0	0	2	0.0
	Total	0	42	1445	268	0	0	1755	
Prod.	**Acc.**	0.0	35.7	63.5	56.3	0.0	0.0		

Table 8. Output product specifications. ‘a’ stands for a year.

Product	**Acronym**	**Unit**	**Other values**
Growing stock volume	GSV	m^3/ha	65533: Non-tree cover 65534: Water 65535: Clouds (or other no data)
Gross primary production	GPP	CO_2t/ha/a	65533: Non-tree cover 65534: Water 65535: Clouds (or other no data)
Net primary production	NPP	CO_2t/ha/a	65533: Non-tree cover 65534: Water 65535: Clouds (or other no data)
Stem volume increment	SVI	m^3/ha/a	253: Non-tree cover 254: Water 255: Clouds (or other no data)

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Figure 5. Growing stock volume (GSV) map in 10 m spatial resolution processed in Forestry TEP for Finland and the Russian boreal forest until the Ural Mountains.

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