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ORIGINAL ARTICLE

A spatial assessment of the forest carbon budget for Ukraine

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Abstract The spatial representation of forest cover and forest parameters is a prerequisite for undertaking a systems approach to the full and verified carbon accounting of forest ecosystems over large areas. This study focuses on Ukraine, which contains a diversity of bioclimatic conditions and natural landscapes found across Europe. Ukraine has a high potential to sequester carbon dioxide through afforestation and proper forest management. This paper presents a new 2010 forest map for Ukraine at a 60 m resolution with an accuracy of 91.6 ± 0.8% (CI 0.95), which is then applied to the calculation of the carbon budget. The forest cover map and spatially distributed forest parameters were developed through the integration of remote sensing data, forest statistics, and data collected using the Geo-Wiki application, which involves visual interpretation of very high-resolution satellite imagery. The use of this map in combination with the mapping of other forest parameters had led to a decrease in the uncertainty of the forest carbon budget for Ukraine. The application of both stock-based and flux-based methods shows that Ukrainian forests have served as a net carbon sink, absorbing 11.4 ± 1.7 Tg C year^{-1} in 2010, which is around 25% less than the official values reported to the United Nations Framework Convention on Climate Change.

Keywords Forest cover · Carbon budget · Carbon sink · Growing stock · Remote sensing

1 Introduction

Despite recent progress in assessing carbon budgets, there is still substantial uncertainty in the estimation of the carbon budget of forest ecosystems (Pan et al. 2011; Shvidenko et al. 2010; Pan

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et al. 2011; Metsaranta et al. 2017; Le Quéré et al. 2017). In addition to the inherent uncertainties in the methods and models used for studying carbon cycling, there are other possible reasons for this uncertainty, which include the absence of forest inventories in some territories, particularly those that are not managed by state forest authorities, the lack of data for some categories of forests, obsolete data in forest inventories, and the existence of territories with rapid changes in forest cover, e.g., caused by disturbances or the encroachment of forests in abandoned agricultural land. Not every country provides comprehensive information about the area or spatial distribution of forests, in particular the distribution of tree species and their age (Schepaschenko et al. 2015), and forest inventories, more generally, lack spatial information about the forests at an appropriate resolution, which hinders the consistent application of a systems approach.

Improving knowledge about land cover and the parameters of forest ecosystems is of high importance for carrying out reliable assessments of emissions and removals from the forestry sector as well as for devising solutions to diverse ecological and forest management problems. Providing accurate data on the spatial distribution of forests represents a substantial step towards gaining a better understanding of full and verified carbon accounting as it is possible to more strictly follow the principles of systems analysis; this is why it represents one of the most promising ways to decrease uncertainties (Schepaschenko et al. 2012; Shvidenko et al. 2015). One way of achieving this is through the use of data from remote sensing. Remote sensing helps to improve carbon budget estimates in several ways, combining top-down and bottom-up approaches as follows. First, satellites (optical, radar, and LIDAR instruments) are already providing reliable estimates of important biophysical parameters of forest ecosystems such as tree canopy parameters, growing stock, above-ground biomass and net primary production (NPP). Measurements of carbon dioxide (CO_2) and methane (CH_4) concentrations in the atmosphere are used for the assessment of the spatial distribution of the land carbon fluxes of these important greenhouse gases using inverse modeling (Oda et al., this issue) based on, e.g., GOSAT (http://www.gosat.nies.go.jp/en/) or OCO-2 (http://oco.jpl.nasa.gov/). Secondly, remote sensing data are indispensable for the delineation of land cover and forests with different tree species and for deriving biometric characteristics such as forest stand height and above-ground volume. Ground information is used for the validation of remote sensing products as well as for assessing these parameters that cannot be identified using remote sensing.

Ukraine, which is the focus of this study, is unique as it is one of the largest European countries and covers a substantial portion of eastern European diversity in natural landscapes. A specific feature of Ukraine is the presence of a transition zone between forest and southern forestless steppe (the xeric belt), where ecosystems are vulnerable to environmental change. In addition, Ukraine has a high potential to sequester carbon through afforestation, since the country has greater than 3 M ha of unproductive abandoned agricultural lands (Schierhorn et al. 2013; Smaliychuk et al. 2016), as well as via other forest management activities (Galos et al. 2013).

The carbon budget of Ukrainian forests has been previously considered in a number of publications. Initial attempts were undertaken by the United States of America sponsored Country Studies Program in the 1990s (Vasilchenko et al. 1998). Several books contain methodologies that follow the requirements of the Intergovernmental Panel on Climate Change (IPCC) (Buksha and Pasternak 2005; Buksha et al. 2008). The forest carbon cycling of some regions has also been considered in detail, e.g., in the forests of the Carpathians mountains (Bun et al. 2004), or the northeastern part of the country (Pasternak 2011). Reported results on forest carbon cycling in Ukraine at the national level (www.seia.gov.ua/seia/doccatalog/document?id=138881) have mostly been based on forest inventory data by administrative regions, which limits the possibility for assessing uncertainties. Spatially explicit information on forest cover and forest parameters derived from remote sensing have not been used in previous assessments of forest carbon cycling in Ukraine (Shvidenko et al., 2014) although methodologies and recommendations for the use of satellite data have been considered in detail (Buksha and Pasternak 2005) and have been used for studying forest change, illegal logging, land abandonment, and carbon sequestration in parts of Ukraine (Kuemmerle et al. 2009, 2011).

Hence the overall objective of this paper is to develop a spatially-explicit assessment of the carbon budget of Ukrainian forests, which is as accurate as possible and includes the quantification of uncertainty. The methodology is based on integrating different recently developed remote sensing products with reference data collected through the Geo-Wiki tool for interpretation of very high resolution satellite imagery. The forest inventory data for 2010 were then corrected based on the remote sensing information. The components of the carbon cycle that cannot be identified from remote sensing (e.g., woody detritus, lateral fluxes) or that require special areal approaches and additional information sources (e.g., logging, fire) were adopted from previous assessments (Shvidenko et al. 2014). The detailed description of the methodology for the assessment of the forest carbon budget is described in the next section. This is followed by the presentation of the results as spatially explicit map products, their impacts on the total carbon budget, and the values disaggregated by bioclimatic region. The results are compared with other recent estimates, and the problems associated with uncertainty are then discussed, followed by the conclusions.

2 Methodology

2.1 The forests of Ukraine

Overall Ukraine is a forest-poor country with a forest cover percentage of less than 16%, which is unevenly distributed over its territory. Forests in Ukraine grow in different bioclimatic zones in the flat part of the country's territory, i.e., the forest zone (Polissya, with a forest cover percentage of 37%), the forest steppe (29%), and the steppe (11%), which form the major land cover type of two mountain systems, i.e., the Carpathians (up to 50% in the mountain regions) and Crimea (with practically no forest outside of the Crimean mountains). These regions differ by species composition, age, origin, and productivity. Coniferous forests cover 42% of the total forest area, with 32% pine (*Pinus silvestris L.*), and 10% spruce (*Picea abies Karst.*) and fir (*Abies alba Mill.*). Hard deciduous species cover 43%, of which oak (*Quercus robur L.*) and beech (*Fagus sylvatica L.*) dominate with 32% of the total forest area. About 32% of forests are young stands, 44% middle-aged, 13% immature, and 11% mature or overmature. On the average, the forests have a high productivity, e.g., the average growing stock over the country is 200 m^3 ha^{-1}(Ukrstateforestproject 2012). More than 50% of the forested area are planted forests.

Ukrainian forests (in addition to those in the mountainous regions) are substantially fragmented with an average area of the primary inventory unit (i.e., the individual forest stand or other categories of forest land) of 2–3 ha, which requires the use of very high-resolution remotely sensed data for detection.

2.2 Methodology workflow

We have used a range of different products derived from remote sensing to estimate the spatially explicit forest carbon budget using the steps outlined in Fig. 1: (1) a forest mask was developed for the year 2010, (2) the spatial distribution of the forest parameters was derived based on available information, and (3) the major components of the carbon budget of the forest ecosystems were estimated, including the uncertainty. Each of these steps is described in more detail below.

2.3 Developing the forest mask

To reduce the uncertainties in the calculation of the forest carbon budget, we have developed a new country-wide forest map at a resolution of 60 m by fusing available data derived from remote sensing with reference data (Hansen et al. 2013; Chen et al. 2014; Shimada et al. 2014a). These individual maps suffer from significant thematic errors, e.g., on Hansen's tree cover map, all the wetlands have been classified as high-percentage forests; on the JAXA (Japan Aerospace Exploration Agency) PALSAR forest mask, some villages or small towns are classified as trees; on the 30 m GlobeLand land cover product, small patches of forest are very often aggregated to a dominant class in a neighboring area, e.g., to agriculture. To create an improved land cover map, we used a spatial analytical method called geographically weighted regression to integrate existing maps with Geo-Wiki reference data to develop a more accurate product. Here, we define reference data to be either in-situ data or data collected by visual interpretation of very high-resolution satellite imagery. The hybrid forest map is then used for the assessment of the carbon budget of the forest ecosystems in Ukraine including uncertainty. The methodology for the creation of the hybrid map and the assessment of the forest carbon budget are described in the sections that follow.

2.3.1 Input layers

A number of new land cover products derived from remote sensing have recently emerged. The overall trend has been towards a higher spatial resolution such as the 30-m resolution

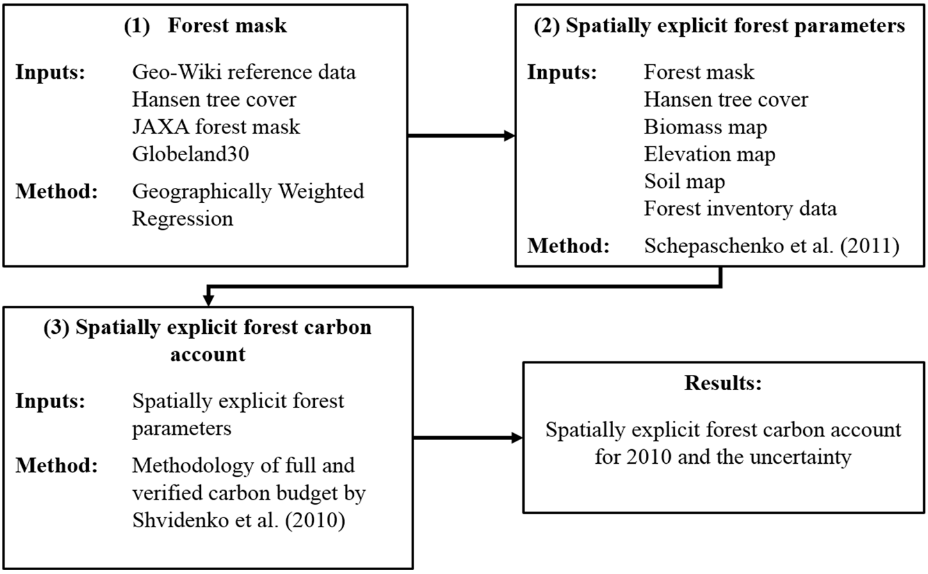

Fig. 1 Scheme for the development of a spatially explicit forest carbon budget

maps of percentage tree cover, as well as tree cover gain and loss by Hansen et al. (2013), and the 30 m GlobeLand land cover product (Chen et al. 2014). These maps were developed from Landsat high-resolution satellite imagery, which has recently become freely available (Wulder et al. 2012). Another product that has become available is forest mask that has been produced by the Japan Aerospace Exploration Agency (JAXA) at a resolution of 25 m (Shimada et al. 2014). Other coarser resolution data sets are also available, e.g., Globcover 2009 with a resolution of 300 m (Bontemps et al. 2011), the MODIS Vegetation Continuous Fields product at 250 m (DiMiceli et al. 2011), etc. Disaggregation of the medium resolution products to a finer resolution increases the uncertainty of estimating the spatial distribution of forests. Therefore, Hansen's tree cover, GlobeLand30, and the JAXA forest mask were chosen for the development of a hybrid forest map at a resolution of 60 m for the year 2010. These products are described briefly below.

The Landsat-based tree cover product is a global forest cover change product for the years 2000–2012 with a spatial resolution of 30 m (Hansen et al. 2013). The product has three components: forest cover 2000, forest gain 2000–2012, and annual forest loss. We created a forest map for 2010 by combining the data from these three products. Starting with the forest map for 2000 as the base year, we adjusted the map by adding forest gains and subtracting forest losses for the time period 2000–2010 to produce a forest map for 2010.

The 30 m GlobeLand30 product for 2000 and 2010 has been developed by the National Geomatics Center of China (Chen et al. 2014). It is based on Landsat imagery in combination with additional information on land resources and imagery from the HJ-1 satellite. The product is freely available and comprises ten land cover classes including forest. We extracted a forest mask for Ukraine from the GlobeLand30 product for the year 2010.

JAXA has produced a 25-m forest mask based on imagery from the Phased Array type L-band Synthetic Aperture Radar (PALSAR) aboard the Advanced Land Observing Satellite "DAICHI" (ALOS) (Shimada et al. 2014).

We have only used forest cover information derived from these three maps. We aggregated these maps to a resolution of 60 m to minimize the spatial errors when comparing the different products, resulting in a percentage forest cover map for each product.

2.3.2 Reference data from Geo-Wiki

Reference data on forest cover were collected using the Geo-Wiki application (Fritz et al. 2012), which aims to validate, correct, and enhance land cover products. Five forestry and remote sensing experts collected the data by visually estimating the percentage of forest cover visible in a 60-m pixel overlaid onto very high resolution Google Earth imagery. To aid the interpreters, each 60-m pixel was further subdivided into nine cells. Here we have defined forest as an area with a minimum tree canopy cover of 25% and a minimum area of 0.5 ha, which corresponds to the official definition of forest in Ukraine (Ukrstateforestproject 2012). This corresponds to slightly more than two cells within each 60-m pixel and a total tree canopy cover of more than 25%.

Figure 2 illustrates how the forest data were collected through a customized application within Geo-Wiki. The training data samples were randomly generated in areas of forest and non-forest using a random stratified design, where the strata were based on the Hansen tree cover map. The final training data set contains approximately 12K pixels of land cover information (presence/absence of forest) for Ukraine.

The validation data have also been collected through Geo-Wiki and the data set includes approximately 4K pixels. The sample has been generated by following the validation guidelines of Olofsson et al. (2014). The sample design is random stratified, where the strata are based on the resultant forest presence/absence map.

2.3.3 Geographically weighted regression

We have chosen geographically weighted regression (GWR) as the method to fuse the three abovementioned land cover products with the training data collected using Geo-Wiki to create a hybrid forest cover map. Lesiv et al. (2016) have shown that GWR performs better than other data fusion methods because GWR estimates the model parameters at each geographical location using a kernel. In addition, the observations are weighted by distance, so those closer to the location of interest will have more influence on the parameter estimates.

The probability of forest presence was then estimated using logistic GWR where the probabilities of correspondence between the Geo-Wiki training data and the input layers were calculated as follows:

$$\operatorname{logit}(P(y_i = 1)) = b_{0(u_i,v_i)} + b_{1(u_i,v_i)}x_{1(i,j)} + b_{2(u_i,v_i)}x_{1(i,j)} + \ldots + b_{n(u_i,v_i)}x_{n(i,j)}, \qquad (1)$$

where $P(y_i = 1)$ is the probability of forest at each location i; log it is a logistic regression; (u_i, v_i) is the two-dimensional vector of location i; $b_{0(u_i,v_i)}$ is the intercept; $b_j, j = \overline{1,n}$ are coefficients of the logistic regression model; $x_j, \overline{j = 1,n}$ indicates the percentage of forest cover in a pixel by global land cover product j, and n is the number of input data sets.

Maps of forest probabilities were converted to forest presence/absence maps by applying a threshold of 50%, following the example of the usage of logistic regression models in Pampel (2000). The hybrid forest map was developed in the R environment, which is a free statistical software with various geographical libraries. The hybrid forest map was then assessed using an

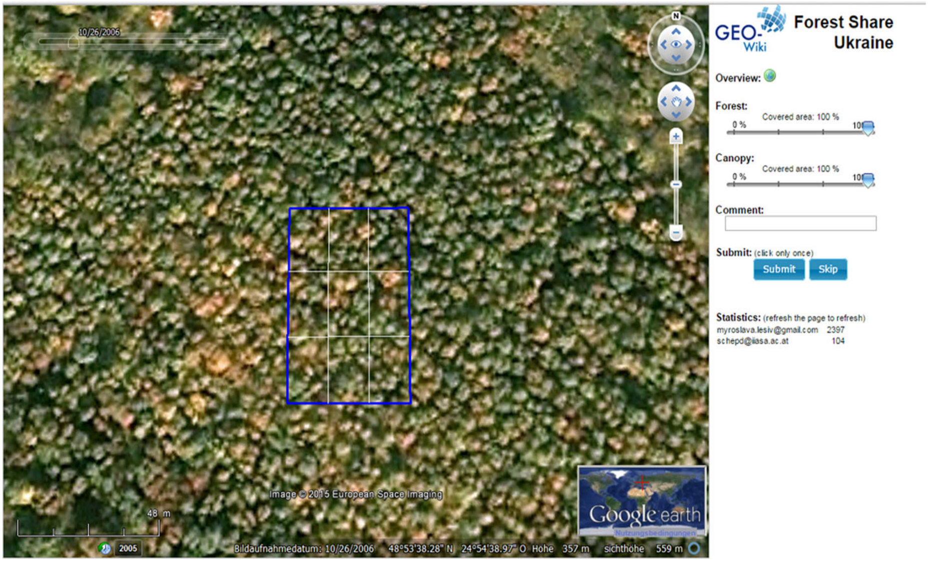

Fig. 2 A customized Geo-Wiki application for collecting forest cover reference data

independent validation data set for Ukraine collected using Geo-Wiki as outlined previously in section 2.3.2.

2.4 Spatially explicit forest parameters

Forest ecosystem parameters include actual forest characteristics that are being recorded and permanently updated by the forest inventory in Ukraine. These parameters include, among others, the tree species, their age, the relative stocking, the site index, the growing stock volume, and the area in ha. These individual stand data are collected by forest enterprises, which are administrative forest units managed by the state. We have used official data for the year 2011, which is the latest available forest database.

The forest ecosystem parameter database has been downscaled to the level of the forest map developed here. For downscaling, we applied the method presented in Schepaschenko et al. (2011). We calculated a suitability index for each pixel pair (i.e., between the forest pixel and the forest inventory database record) within the territory unit (or forest enterprise). A forest pixel is a pixel of the forest map that is covered by forest. We used the following formula:

$$S_{\mathrm{ts}} = \frac{1}{q}\left(\sum_{j=1}^{q}\left(x_{\mathrm{tj}}^{\mathrm{norm}} - x_{\mathrm{sj}}^{\mathrm{norm}}\right)^2\right)^{\frac{1}{2}} \tag{2}$$

$$x_j^{\mathrm{norm}} = \frac{x_j - x_{j,\min}}{x_{j,\max} - x_{j,\min}} \tag{3}$$

where S_{ts} is the suitability index; t is the forest pixel; s is the record from the forest database; q is the number of parameters; and $x_{j,\ \max}$, $x_{j,\ \min}$ are the maximum and minimum values of parameter j within a certain area (i.e., the forest enterprise).

To calculate the suitability indices, we used diverse sources of information as parameters, including estimates from leading experts in forestry, who have experience of Ukrainian forests, to derive the decision rules regarding the following:

• The ecological pattern of tree species distributions in mountainous regions based on their preferred elevation and aspect

• The site index associations with slope and altitude

• The distribution of tree species depending on soil type

As explanatory layers, we used the following remote sensing products:

• The Hansen percentage tree cover map for 2010 (Hansen et al. 2013), created from the available layers as described previously, to link tree cover to the relative stocking from the forest inventory records

• A soil map of Ukraine (Krupsky and Polupan 1979), to link soil types to tree species from the database, as certain tree species prefer a certain soil type

• A biomass map (Gallaun et al. 2010) to calculate the growing stock volume

• A digital elevation model from SRTM (Shuttle Radar Topography Mission) (Werner 2001) since the distribution of tree species in mountains is very well correlated with elevation

The resultant suitability index varies from 0 to 1. It can be interpreted as the distance between objects (i.e., the forest pixel and the database record) within the space of parameters. The lower the value of the index, the more suitable is the current piece of territory. Each forest record in the database was assigned to the most suitable pixel within each forest enterprise.

2.5 Estimating the parameters of the forest carbon budget

For assessment of the carbon budget of Ukrainian forests, a methodology for a full and verified carbon budget was used, which was developed by the International Institute for Applied Systems Analysis (Shvidenko et al. 2015). The methodology is based on a system combination of flux-based and stock-based methods. The stock-based method estimates the change in the carbon stock of carbon pools as

$$\Delta C = \Delta \mathrm{LB} + \Delta \mathrm{WD} + \Delta S \tag{4}$$

where ΔLB, ΔWD and ΔS are changes in the carbon stocks of live biomass, woody detritus, and soil, respectively, while the flux-based method has the following form:

$$\mathrm{NBP} = \mathrm{NPP}{-}\mathrm{HSR}{-}\mathrm{DEC}{-}\mathrm{HARV}{-}\mathrm{DIST}{-}\mathrm{LAT} \tag{5}$$

where NBP is net biome production; NPP is net primary production; HSR is heterotrophic soil respiration; DEC is the flux due to decomposition of dead wood that remains in the forest; HARV are the fluxes due to harvest and international trade of wood products; DIST is the flux caused by disturbances, and LAT are lateral fluxes to the hydrosphere and lithosphere. Both of these methods have strengths and weaknesses (e.g., Shvidenko et al., 2010, 2015). For example, the dynamics and variability of soil carbon content do not allow for the reliable monitoring of soil carbon changes in the stock-based method, while the NPP flux can be estimated much more accurately using the biomass change approach. This is why we have used both methods together in a complimentary way.

Live biomass (LB) was defined using a multi-dimensional regression of biomass expansion factors (R_{fr}) by species, geographical regions (where relevant), and LB components (Shvidenko et al. 2007) as follows:

$$R_{\mathrm{f}r} = {}^{M_{\mathrm{f}r}}/_{\mathrm{GS}} = a_0 \times A^{a_1} \times \mathrm{SI}^{a_2} \times \mathrm{RS}^{a_3} \times \mathrm{EXP}(a_4 \times A + a_5 \times \mathrm{RS}) \tag{6}$$

where R_{fr} is the ratio of the mass of individual components of LB (stem wood over bark; crown wood; foliage; roots) to growing stock volume; M_{fr} is the mass of individual components of LB, dry matter or carbon units, t ha^{-1}; GS is the growing stock volume, m^3 ha^{-1}; A is the average age of stands in years; SI is the site index; RS is the relative stocking, and a_1, a_2, ... a_5 are the regression coefficients. The mass of LB is then defined as $\mathrm{LB}_{\mathrm{fr}} = R_{\mathrm{fr}} \times \mathrm{GS}$ and $\mathrm{LB}_{\mathrm{tot}} = \Sigma \times \mathrm{LB}_{\mathrm{fr}}$, where $\mathrm{LB}_{\mathrm{tot}}$ is the total LB of an individual forest ecosystem. Equation (6) is based on extensive field experiments (using destructive sampling) collected in a database that includes more than 11,000 sample plots for temperate and boreal forests (Schepaschenko et al. 2017b). When Eq. (6) is applied to multiple species, there is no systematic error. Moreover, such an approach can estimate LB within a 15% error band (CI 0.9) for an individual forest stand if the GS is defined within the officially required maximum error of 12% (Shvidenko et al. 2014). The yearly change in the LB stock (i.e., current increment by LB) was defined as the difference between the LB of two consecutive years.

The last two components of Eq. (4) cannot be measured by remote sensing directly. The change in the woody detritus stock was recalculated based on forest area change, forest inventory data, and a database of direct in situ measurements; this stock included dry standing trees (snags), dry branches of living trees, logs, and stumps. These data were calculated for 2000–2010. Taking into account the substantial uncertainty in the input data, the calculation was done at the level of administrative regions. Satisfactory data on the dynamics of soil carbon in Ukrainian forests are absent. We used the average data published for European forests (Kramer and Mohren 2001; Mund and Schulze 2006; Kutsch et al. 2010) for corresponding tree species in similar climate conditions to Ukraine, which were in line with the limited data available for Ukraine (Pasternak 2011).

NPP was defined by a semi-empirical method described in Shvidenko et al. (2007). It is calculated based on regionally distributed models of biological productivity, which combine models of growth and LB dynamics. Within this method, NPP is considered to be the difference in total productivity of LB for two consecutive years, taking into account the turnover of fine roots and foliage, damage by wind, insects, harvest, etc. This method does not have any recognized biases compared to a direct aggregation of results from field measurements, which do not account for some important components of carbon turnover (e.g., root exudates, volatile organic compounds). The uncertainty in the NPP was defined in an independent way, i.e., through a correlation between the current increment of LB and NPP.

Heterotrophic soil respiration (HSR) was calculated using the approach presented in Mukhortova et al. (2015) by groups of soil types i and dominant tree species j as

$$HSR(i,j) = TSR(i) \cdots PHSR\ (i,j) \cdots A\ (i,j). \tag{7}$$

where TSR is total soil respiration; PHSR is the percentage of HSR in TSR, and A is the area of the dominant species.

DEC was assessed based on zonal coefficients of decomposition that were averaged based on measurements in Ukrainian forests and regions of similar climatic conditions and forest types of the Eurasian temperate zone. The amount of harvested wood, as well as data on natural disturbances, were taken from the official statistics of the State Agency of Forest Management of Ukraine. Natural disturbances included fire, impacts of insects and diseases, and the impact of unfavorable weather conditions. Carbon fluxes caused by forest fire were assessed by an approach presented in Shvidenko et al. (2014). The assessment of the impacts of biogenic factors and unfavorable weather conditions on productivity and the health status of forests was based on an estimation of the forest-pathological state of Ukrainian forests by administrative region for previous years and forecast to 2020 (Ustsky et al. 2010; Ustsky 2011). The forest-pathological state was quantified using the percentage of mortality for six levels of severity due to forest-pathological processes.

Spatially-explicit regional estimates of the removal of carbon in the hydro- and lithosphere in Ukraine are absent. We used published data for the temperate forests of the Northern hemisphere, which provide average values in the range of 1.5–2% of NPP (e.g., Dolman et al. 2012).

The stock- and flux-based methods were used to produce independent estimates of the carbon cycle of Ukraine's forests. The uncertainties in these methods were calculated based on the application of error propagation theory: for a function $y = f(x_1, x_2, ..., x_k)$, where x_i ($i = 1, ..., k$) are stochastic variables with standard errors m_i, the standard error of y is defined as

$$m_y^2 = \sum_{i=1}^{k} \left(\frac{dy}{dx_i}\right)^2 + 2\sum_{i>j} \left(\frac{dy}{dx_i}\right)\left(\frac{dy}{dx_i}\right) r_{ij} m_{x_i} m_{x_j}, \tag{8}$$

where r_{ij} is the correlation coefficient between x_i and x_j, and $\mathrm{dy}/\mathrm{dx}_i$ are the partial derivatives of y by x_i.

When $r_{\mathrm{ij}} < 0.2–0.3$, which is typical for the majority of the estimated parameters, the use of only the first component of the right part of Eq. (8) does not change the level of the final uncertainty substantially; thus, in appropriate cases, we used Eq. (8) in a simplified form, i.e., assuming statistical independence of the input variables.

A specific feature of the carbon accounting and estimation of uncertainties that are presented in this paper is the use of a forest inventory database for forests in Ukraine. This database contains biometric characteristics of ca 3.6×10^6 individual stands, i.e., primary inventory units, from about 2×10^3 for larch to over 10^6 for oak stands. This has had an impact on the specifics and size of the uncertainties because it has practically eliminated the sampling error in some cases. We have provided calculations of these parameters for forests with the ten major dominant species, which cover about 95% of the forest area in Ukraine. In the calculations, the relevant data about the rest of the tree species that cover the remaining area were added to the species with similar bioecological properties.

3 Results

3.1 A hybrid forest map and forest parameters for Ukraine

The first output in this study is the hybrid forest map for the year 2010 for Ukraine and the forest ecosystem parameters. These are required as inputs for the calculation of the spatially explicit carbon budget. The hybrid map represents the first forest map for this country at a 60-m resolution. The overall accuracy of the map is $91.6 \pm 0.8\%$ (CI 95%). Table 1 presents a summary of the accuracy estimates of the new forest mask and the input maps used in its development. The differences in the accuracy estimates between each possible pair of maps are statistically significant (p values < 0.01) (Foody 2004).

Bilous et al. (2017) estimated the accuracy of several forest maps for 45 km^2 of the Snovsk test area in the Ukrainian Polissya region. They have shown that our hybrid map performs the best (user's accuracy 92%, producer's accuracy 81%) compared to other global data sets presented in this study.

The total area of forest was calculated to be 8.7 ± 0.2 M ha (CI 95%) while the official statistics report 9.6 M ha of forested area in Ukraine (Ukrstateforestproject 2012). There are different potential reasons for this inconsistency. Electronic maps and databases are only available for 8.5 M ha in Ukraine. The rest is represented by forests that are not managed (7.5%) and another 6% that belong to more than 30 different "non-forest" stakeholders (such as the Ministry of Defense and different administrative bodies) with a low or practically absent forest management. The last inventories of these forests were dated around the 1990s, and their real state may be substantially different from the inventory records. In addition, official Ukrainian statistics do not take forested areas on abandoned agricultural land of ca 3 M ha into account, which are largely in the forest steppe and steppe regions. The process of the impoverishment of forests in the southern forest steppe and steppe, particularly of protective

Table 1 Overall accuracy estimates of the final hybrid forest map and the input forest maps

Maps	Overall accuracy %	P values
Hybrid forest map	91.6	< 0.01
GlobeLand 30 m	88.0	< 0.01
Hansen's forest map	86.7	< 0.01
JAXA's PALSAR forest map	84.7	< 0.01

forests and shelterbelts on agricultural land, has been repeatedly reported (Fourdichko et al. 2006). The new map reports forested areas for the southern administrative regions (oblasts) that are substantially less than the corresponding forest inventory data, i.e., up to 30% less, while the regions with forest zones (i.e., Polissya and Carpathians) have similar areas on the map when compared with the forest statistics; sometimes more areas are recorded than in the forest inventory. Indeed, the remote sensing products used in the production of the input forest maps may not recognize narrow shelterbelts in the south, young forests, substantially degraded forests, and afforestation of abandoned agricultural land. Issues associated with mapping of dryland forests are also discussed in Schepaschenko et al. (2017a). Therefore, the mapped forest area is smaller than the forest area estimate. However, the area of such forests is small, i.e., several percent by region. In addition, the new forest map might consider other tree covered areas (e.g., gardens, parks in settlements, etc.) as forests if their canopy cover exceeds the minimum threshold.

From the forest map, we have developed the following spatially explicit forest ecosystem parameter maps: the spatial distribution of tree species, the spatial distribution of total biomass, and the spatial distribution of NPP. The spatially explicit map of dominant tree species (Fig. 3) is the first tree species map at such a fine resolution and with such a detailed nomenclature, fully covering Ukraine. It shows a good spatial distribution of tree species in the mountainous regions of Ukraine, in particular, for beech and spruce trees. However, the spatial distribution of tree species on flat areas has some noise. This map (Fig. 3) also captures dominant tree species by forest enterprises very well.

The accuracy of our tree species map for the Snovsk test area (Bilous et al. 2017) was estimated as 71%, while the overall accuracy of the European tree species data set (Brus et al. 2012) was only 36% for the same area. Our growing stock volume estimation was again the most reliable when compared to any other global or regional data sets (Bilous et al. 2017).

Figure 4 highlights the forest areas with the highest biomass values such as the Carpathians, and with the lowest biomass, i.e., the Volyn region in Ukraine in the northern and southern regions.

Figure 5 shows the spatial variation of NPP of Ukrainian forests. The patterns are very similar to the spatially explicit forest biomass map (Fig. 4).

3.2 The forest carbon budget and its uncertainties

Using the hybrid forest map and the methodology outlined in Section 2.3, the results of the assessment of the LB of Ukraine's forests, as a crucial component of the stock-based method, is presented in Table 1. LB is aggregated by dominant species and for the country as a whole. The LB stock is assessed at 707.7 Tg C, or 81.2 t C ha^{-1}. Trees comprise 95% of carbon of the total LB; 82% are in above-ground LB; 68% are in stem wood, and 17% are in roots. Only 5% of the carbon in forest ecosystems are in the understory and the green forest floor. Overall, such proportions are typical for temperate forests of high productivity.

The calculated uncertainty in total LB includes errors in the regressions of the biomass expansion factors, the growing stock volume, and the area (Table 2). If LB is expressed in units of dry matter, the final error is estimated at ± 3.3%. If the error from the recalculation of the LB in carbon units is added, where we used an additional error of ± 1.5% in this estimation, then the final error is ± 3.6%. Here and below these estimates are to one standard error unless otherwise stated. Because the LB was calculated for each forest stand in the database, the

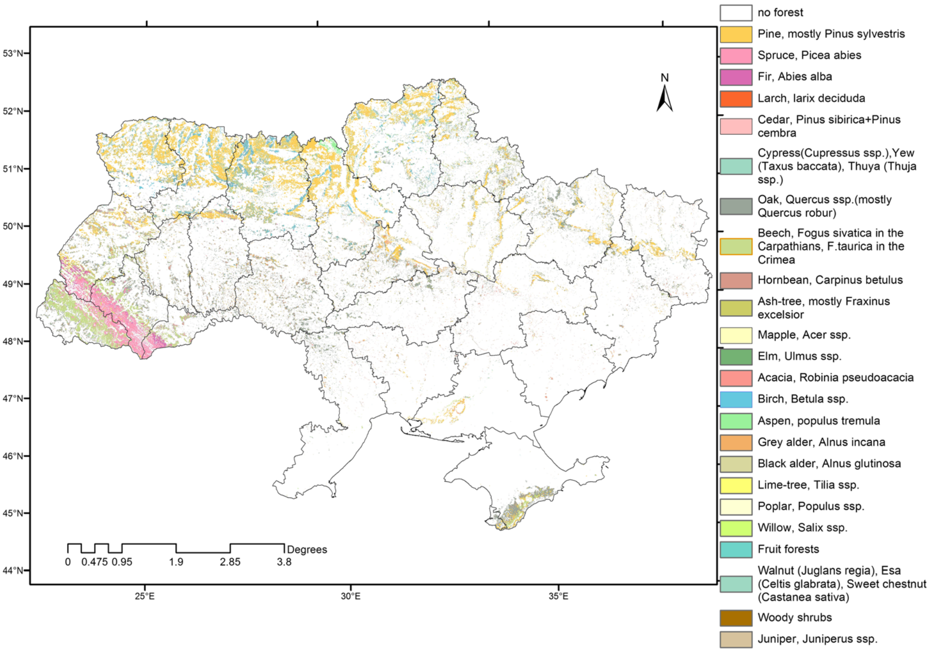

Fig. 3 The spatial distribution of dominant tree species for 2010

impact of the uncertainties of the biomass expansion factor regressions on the uncertainties of the average values of LB by tree species was very small.

The total volume of woody detritus is estimated at 141.3 M m^3 (including 56% in dead trees and snags and 44% in logs). Using an average specific gravity of 0.35 for snags and

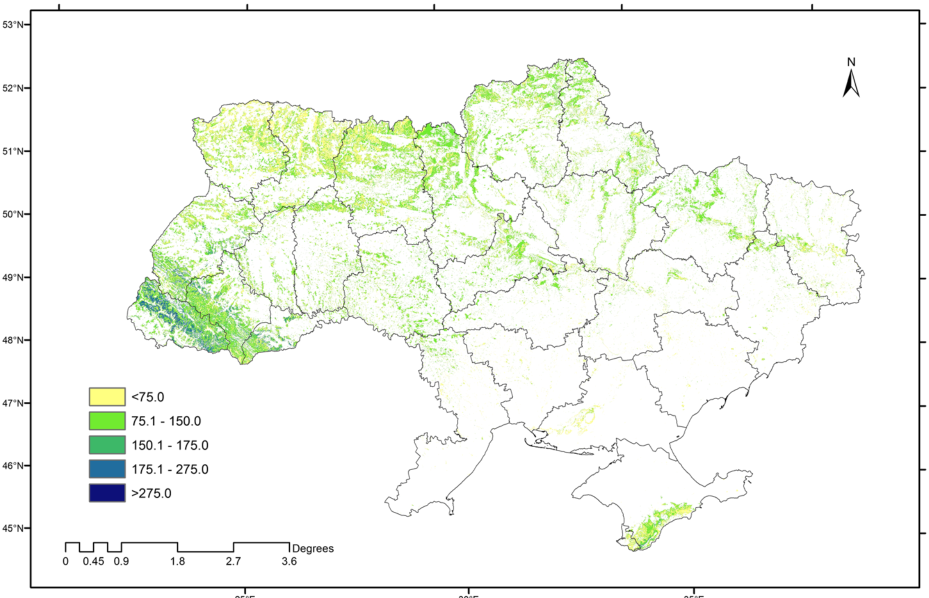

Fig. 4 Biomass map for 2010, t C ha^{-1}

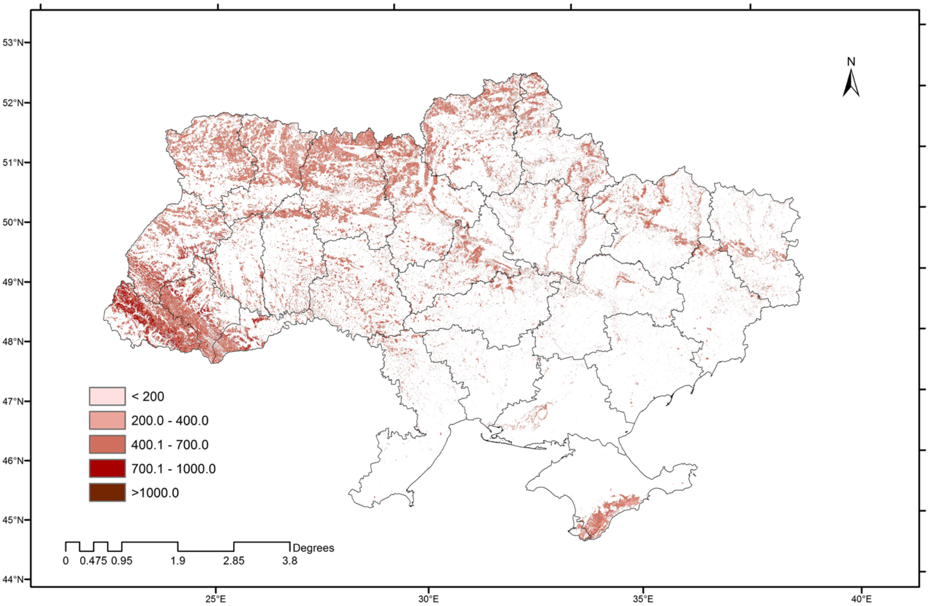

Fig. 5 Net primary production (NPP) of Ukrainian forests for 2010, g C m^{-2} $year^{-1}$

0.25 Mg d.m. m^{-3} for logs plus an assumption of 50% carbon content in the dry matter, then the carbon stock in woody detritus can be estimated at 21.7 Tg C, or 3.1% of the total stock of carbon in LB. Reliable estimates of woody detritus dynamics are possible only based on a long period of observation. Assuming that the share of woody detritus to the total LB does not change over a short period (i.e., 2 to 3 years), the stock change in the woody detritus will increase to 1.56 Tg C $year^{-1}$ (which is 3.1% of the LB annual increment; see Table 3). Assuming that the standard error of this change is 20%, we obtain a sink in dead aboveground wood of 1.56 ± 0.32 Tg C $year^{-1}$.

Despite a number of publications on the impacts of forests on soil carbon under afforestation in Ukraine, there are no systematic inventories of the dynamics of soil carbon in forests that have not undergone large scale disturbances. The official reporting of Ukraine to the

Table 2 Total LB of Ukrainian forest by dominant species

Species	Area, 10^3 ha	GS, 10^6 m^3	R_{tot}	m_{Rtot}	LB, Tg C	m_{LB}, Tg C
Pine	3049.0	721.7	0.6268	0.0215	226.2	8.54
Spruce	662.0	209.4	0.6570	0.0204	68.6	2.35
Fir	133.5	35.8	0.6081	0.0204	10.9	0.41
Larch	9.4	2.1	0.7033	0.0235	0.7	0.03
Oak	2515.3	422.4	0.9623	0.0307	203.2	7.13
Beech	759.1	232.6	0.9699	0.0317	112.8	4.06
Acacia	203.5	13.9	1.2757	0.0389	8.8	0.30
Birch	690.1	97.0	0.8097	0.0264	39.3	1.41
Aspen	158.8	25.1	0.7620	0.0234	9.6	0.33
Alder	531.7	82.9	0.6602	0.0224	27.4	1.03
Total	8712.5	1842.9			707.7	25.62

GS, growing stock volume; R_{tot}, biomass expansion factor for the total ecosystems LB ($R_{tot} = R_{stem} + R_{branches} + R_{foliage} + R_{roots} + R_{understory} + R_{gff}$); *LB*, live biomass; *m*, standard error

Table 3 Assessment of NPP and the uncertainty

Species	NPP, Tg C $year^{-1}$	NPP, g C m^{-2} $year^{-1}$	s_{NPP}, g C m^{-2} $year^{-1}$	$Z_{LB,\ tot}$, 10^3 t C	$m_{Z_{LB,tot}}$, 10^3 t C	s^2_{res}, $(g\ C)^2$ m^{-4} $year^{-2}$	s^2_{regr}, 10^6 t C	m_{NPP}, g C m^{-2} $year^{-1}$
Pine	13.23	434	45	2518.5	122.2	158	60	14.8
Spruce	3.83	585	65	1068.5	46.9	330	188	22.8
Fir	0.61	460	53	161.0	7.6	219	82	17.3
Larch	0.06	653	120	18.1	0.9	1123	121	35.3
Oak	13.28	528	55	1765.7	79.6	971	87	32.5
Beech	5.33	702	69	879.1	40.6	1528	240	42.0
Acacia	0.86	425	59	201.4	8.7	1117	58	35.7
Birch	3.43	497	50	610.1	28.2	1156	144	36.0
Aspen	0.99	622	73	228.0	9.9	1711	328	45.2
Alder	2.24	422	35	242.5	11.6	393	45	20.9
Total	43.86	504	54	7692.9	356.1	–	–	27.9

s_{NPP}, the standard deviation of NPP; $Z_{LB,\ tot}$, the total current increment; $m_{Z_{LB,tot}}$, the standard error of $Z_{LB,\ tot}$; s^2_{res}, the variance of the residuals of NPP; s^2_{regr}, the variance generated by the uncertainties of average $Z_{LB,\ tot,}$by tree species; m_{NPP}, standard error of NPP

Table 4 Assessment of heterotrophic soil respiration and its uncertainty

Soil groups	Area	m_{area}	TSR	m_{TSR}	HSR	m_{HSR}	HSR average	m_{HSR}	HSR
	10^3 ha		g C m^{-2} $year^{-1}$		%		g C m^{-2} $year^{-1}$		Tg C $year^{-1}$
Luvisols and Greyzems	2421.3	99.3	569	18.6	48.7	1.2	277	16.0	6.71
Gleysols	974.9	40.0	619	47.9	49.1	1.8	304	28.9	2.96
Histosols	646.6	26.5	525	20.5	48.8	1.8	256	17.3	1.66
Cambisols and Metamorphic soils	1361.8	55.8	645	26.7	49.9	1.2	322	20.3	4.38
Phaeozems, Histosols and Leptosols	722.4	29.6	1103	65.4	48.2	1.8	532	43.2	3.84
Chernozems and Kastanozems	2111.1	86.6	538	34.3	47.6	1.8	256	21.7	5.40
Fluvisols	206.4	8.5	1140	41.8	48.2	1.8	550	36.6	1.14
Calcisols and Solonetz	215.7	8.8	434	21	46.7	1.8	203	15.1	0.44
Leptosols	52.3	2.1	666	34.3	39.8	1.2	265	19.2	0.14
Total	8712.5	357.2	–	–	–	–	306	23.7	26.67

HSR, heterotrophic soil respiration; *TSR*, total soil respiration; *m*, standard error for different variables in the table

Secretariat of the UNFCCC uses an assumption that soil carbon stock does not change in those forests that remain forests for the period of the assessment (www.seia.gov.ua/seia/doccatalog/document?id=138881). However, in-situ measurements do not corroborate this. The modeling calculations for European forests show that approximately 70% of carbon inputs are accumulated in LB and woody detritus and 30% in soil including litter (Liski et al. 2002; Nabuurs et al. 2003). Other studies estimate the accumulation of carbon in the soil of forest ecosystems to be in the range of 10–50 g C m^{-2} $year^{-1}$ (Mund and Schulze 2006; Kutsch et al. 2010). According to Kramer and Mohren (2001), while the net annual accumulation of carbon in the soil of European forests is 0.05 kg C m^{-2} $year^{-1}$. The first approach yields 2.3 Tg C $year^{-1}$, while the second produces estimates that range from 0.9 to 4.4, or on average 2.6 Tg C $year^{-1}$. Taking into account the specifics of Ukrainian forests (i.e., harvested and fire areas, use of woody detritus for fuel, and area of planted forests), we have used a conservative estimate of 75% of the average of the above two approaches (1.88 Tg C $year^{-1}$). Assuming an error of 50%, we would obtain an annual input to the woody detritus pool of 1.88 ± 0.94 Tg C $year^{-1}$. Following Eqs. (1) and (4), the net ecosystem carbon budget (NECB) of Ukrainian forests is estimated by the stock-based method to be 11.1 ± 1.4 Tg C $year^{-1}$, which is an error of 12.6%.

With respect to the flux-based method, we estimated two major fluxes: NPP (Table 3) and HSR (Table 4). Similarly to LB, NPP was defined for each individual stand. The total NPP was determined to be 44.0 Tg C $year^{-1}$, i.e., the average for Ukraine is 504 ± 28 g C m^{-2} $year^{-1}$ (with an error of ± 5.6%). The spatial variability of NPP is high (Fig. 5). The uncertainty in NPP was estimated in an independent way, based on regressions between the average increment of LB and NPP by dominant tree species. The current increment of total LB was calculated as the difference in the total stock of LB by individual stands with an aggregation by dominant species for two consecutive years and was estimated to be 7.69 Tg C $year^{-1}$. The regressions were calculated separately for coniferous species as follows:

$$y = 1931 \cdot x + 2488, R^2 = 0.92, RMSE = 15 \tag{9}$$

and for deciduous species as:

$$y = 2920 \cdot x + 2694, R^2 = 0.68, \mathrm{RMSE} = 55 \tag{10}$$

where x is the yearly increment by total LB by individual species (t C yearr^{-1}), and y is the average NPP by species. The uncertainty in the NPP was calculated by summing the variance of the increment using Eq. (8) and the regression Eqs. (9–10). The variance of the residuals was estimated as $s^2_{\mathrm{res}} = s^2_{\mathrm{tot}}\left(1{-}R^2\right)$.

The means and standard errors of soil respiration (SR) were calculated based on a database of SR measurements. The estimate was calculated as 26.7 Tg C year^{-1}, or 306 g C m^{-2} year^{-1}. According to Eqs. (5) and (7), the uncertainty was calculated using the variance of TSR, the share of HSR in the total soil efflux, and the area covered by the dominant species. Finally, the uncertainty of SHR was estimated to be 7.7%, i.e., 306 ± 24 g C m^{-2} year^{-1}, or 26.7 ± 2.1 Tg C year^{-1}. SHR comprises ~60% of NPP, and the ratio between NBP and NPP is 0.21. The rather high uncertainties in HSR follow from the lack of knowledge about soil processes in Ukrainian forests and the absence of systematic and detailed information on soils. The database on SR only contained a few measurements made in Ukrainian forests; the scale of the available soil map was coarse (i.e., 1:2.5 M), and the relevant soil horizon indicators were weakly quantified.

The results of the total carbon budget for forest ecosystems in Ukraine estimated by the flux-based method and using the hybrid forest map is presented in Table 5.

The fluxes in Tables 3 to 5 that have not been derived from remote sensing have been adapted from a previous assessment (Shvidenko et al., 2014) and recalculated with respect to the areas of the hybrid map.

The uncertainty in these relatively small fluxes are as follows: DEC ± 20%, HARV ± 15%, DIST ± 33%, and LAT ± 57% (where all values are rounded to integer numbers). Together this results in a final uncertainty in the yearly value of NBP defined by the flux-based method as 11.8 ± 3.2 Tg C year^{-1}, i.e., the relative error is ca 28%, which to a substantial extent is explained by the high annual variability in the two major fluxes (NPP and HSR) and insufficient soil information in particular. Much more accurate results from the flux-based method will be produced if longer time periods are used, e.g., 12–15% for a 5-year period, assuming that the assessment does not have uncontrolled biases.

Table 5 Carbon budget of Ukrainian forests based on the flux-based method

Bioclimatic region	Area,K ha	Carbon fluxes, g C m^{-2} year^{-1}, the totals in Tg C year^{-1}						
		NPP	HSR	DEC	HARV	DIST	LAT	NBP
Polissya	3554.4	453	327	11	34	21	5	55
Forest steppe	2562.1	531	283	7	23	17	8	193
Steppe	608.9	487	263	3	3	26	5	187
Carpathians	1727.3	589	325	14	32	9	12	197
Crimea	259.9	442	273	6	2	12	6	143
Total	8712.5	44.0	26.7	0.9	2.4	1.5	0.6	11.8
Average, g C m^{-2} year^{-1}	–	504	306	10	27	18	7	135
Uncertainty, g C m^{-2} year^{-1}	–	± 28	±24	±2	±4	±6	±4	±38

NPP, net primary production; *HSR* heterotrophic soil respiration; *DEC*, the flux due to decomposition due to dead wood that remains in the forest; *HARV*, the flux due to harvest and international trade; *DIST*, the flux caused by disturbances; *LAT*, lateral fluxes to the hydrosphere and lithosphere; *NBP*, net biome production

Overall, the two approaches lead to the conclusion that Ukrainian forests serve as a net carbon sink in the range from 11.0 ± 1.4 (stock-based method) to 11.8 ± 3.2 Tg C year^{-1} (flux-based method), or on average 11.4 ± 1.7 Tg C year^{-1} (or 131 ± 20 g C m^{-2} year^{-1}). The sink differs by bioclimatic zone, i.e., from 55 g C m^{-2} year^{-1} in Polissya to 197 g C m^{-2} year^{-1} in the Carpathians. This diversity is explained by climatic and forest type drivers as well as by the intensity of the harvest and the extent and severity of natural disturbances.

4 Discussion

One of the key results from this study is the fact that the current forest inventory system in Ukraine does not correctly reflect areas of national forest, which impacts the reliability of the estimates of almost all forest ecosystem services including carbon sequestration. This is a rather unexpected result because the existing system is based on the principles of continuous forest inventory and should provide the annual estimation of all forest parameters. The difference between official forest inventory data (9573.9×10^3 ha) and the hybrid forest map ($8712.5 \pm 226.2 \times 10^3$ ha) is large (~ 9%), and the spatial distribution shows an important feature, i.e., while regions of the forest zone and mountains have forest areas that are close to the inventory data, the areas in the regions of the southern forest steppe and steppe differ by up to 30% or more. This cannot be explained by the uncertainty from the remote sensing assessment. The resolution of the hybrid forest map is sufficiently fine such that substantial biases are avoided. The study also shows that the integration of relevant remote sensing products through advanced spatial analytical methods such as geographically weighted regression in combination with reference data collected through Geo-Wiki allows us to provide a forest cover map for a specific date with a satisfactory level of accuracy. The independent use of the flux- and stock-based methods of carbon accounting resulted in a rather low level of uncertainty, i.e., ± 3.6%. This high level of accuracy has positive implications for acceptability by policy makers (Shvidenko et al. 2010).

There have been very few results published in the past for the entire country. These are limited to the official reporting of Ukraine to the Secretariat of the IPCC. The 6th National communication of Ukraine (http://unfccc.int/national_reports/items/1408.php) reported a net carbon sink of 161.6 g C m^{-2} year^{-1} for the last few decades, which is about one fifth higher than the estimate found in this study (135 ± 38 g C m^{-2} year^{-1}). The National Communications are based on data from the National Cadastre of anthropogenic emissions and removals, which is updated periodically (www.seia.gov.ua/seia/doccatalog/document?id=138881); for 2010, the net carbon sink was estimated at 146 g C m^{-2} year^{-1}. These results were based on the IPCC methodology, the official forest inventory data, and the assumption that the amount of carbon in the soil of forested areas has not changed over time. In a model-based approach for European countries, Schulze et al. (2010) estimated the average sink for Ukrainian forests to be 138 g C m^{-2} year^{-1}, which is ~ 5.4% higher than the estimate produced in this study. Using the flux-based method, Shvidenko et al. (2014) estimated the sink to be 115 ± 29 g C m^{-2} year^{-1} (or 12% lower than the result found in this study) using forest inventory data aggregated by administrative units. This study also reported the result of applying the stock-based method where the dynamics of LB and dead wood were assessed directly, and changes in soil carbon were based on the aggregation of available empirical data. The estimate was 108 g C m^{-2} year^{-1}, or about 17% lower than the carbon sink estimated by the stock-based method in this study. Overall, the reported results of the carbon sink per unit area vary, but in a relatively limited range.

The carbon sink was recently assessed using a system-based approach for forests in 25 countries of the EU, resulting in 75 ± 25 g C m^{-2} year^{-1} and an NBP to NPP ratio of 0.15 (Luyssaert et al. 2010). This is substantially less than our estimates for Ukraine (131 g C m^{-2} year^{-1} and 0.21, respectively). However, it is necessary to note that Ukraine has about 50% of protected forests with a very limited regime of wood harvesting. In addition, we used official data for the assessment of the amount of harvested wood. These data are biased because they do not take into account illegal harvesting in Ukraine, which is substantial, i.e., up to 1.0–1.2 M m^3 year^{-1} (Kiiko 2009; Kuemmerle et al. 2009). Note that in order to exclude the impact of differences in the forest area, we compared the average values of the carbon sink. The differences between the estimates of the total carbon sink for the entire country are clearly higher and could reach up to 20–25% due to the differences in forest area. Hence, the above comparisons include some inconsistencies because different studies have used different methods and different information and were sometimes related to different time periods.

Only one of the above cited studies for Ukraine attempted to assess the uncertainty in the intermediate and final results, which were lower than those reported in this study (Shvidenko et al. 2014). However, this study assumed that the forest inventory presents accurate data about the area of forests in Ukraine. As we have shown here, this does not correspond to reality. The 2010 forest map produced here clearly indicates a lower forest area in Ukraine, particularly in critical growing conditions. This process can relate to both ongoing climate change and decreases in forest governance due to the complicated political situation in the country and military operations in the southeast. Thus, more research is required for providing more accurate estimates of this critical process of change.

Note that the uncertainties in the carbon budget assessment of this study should be used with some caveats. First, the calculation schemes of uncertainty assume that all initial data, empirical aggregations, and semi-empirical models that are used do not have statistically significant biases. To a significant extent, this seems true with respect to the models and the calculation schemes used, the adequacy of which has been controlled by statistical analysis. However, such a statement with respect to the initial data from the forest inventory may be an oversimplification in several important cases, e.g., connected to unknown uncertainties of forest inventory data. Secondly, all considerations of uncertainties are based on normal distributions. An analysis of the major inputs and the calculated intermediate and final results shows that the majority of distributions are similar to a normal (mostly Gram-Charlier) distribution. Hence, this assumption will not have a significant impact on the conclusions. Thirdly, different methods define different indicators, e.g., the flux-based method produces NBP, while the stock-based approach produces the NECB. Fourth, some of the calculations are based on the forest inventory, which is missing around 9% of Ukrainian forests. Covering this gap through analogs will introduce some unknown errors, but these should be relatively small. Finally, all the calculations include the limited use of expert estimates for practical reasons, which introduces some subjectivity into the analysis.

It is important to understand that a full carbon account of forest ecosystems is an ill-defined and hence fuzzy problem whose membership functions are inherently stochastic. This means that the uncertainty arising from any individual method of studying the carbon cycle is inevitably incomplete because it does not contain structural uncertainty, which could be significant. Any judgment about either total uncertainty or the “uncertainty of uncertainties” requires additional information that can only be provided by independent results obtained from other methods (Shvidenko et al. 2010, 2015). Carbon accounting by other methods (such as landscape and global vegetation models, eddy covariance, and direct assessment of carbon cycle parameters by remote sensing) has either not been undertaken in Ukraine, or the spatial resolution of the global products has been too coarse for the reliable assessment of uncertainties in the past. However, the above results from recent inventory studies do present some indirect evidence for judging the full uncertainties of the account.

This study has policy and forest management applications. It demonstrates that even in countries with a rather well-organized forest inventory such as Ukraine, official statistics may be partially obsolete and biased. As shown in recent studies, the national forest information reported to FAO's Forest Resource Assessment is very uncertain for many countries (Schepaschenko et al. 2015), and novel methodologies, which are based on remote sensing within an applied systems analysis approach, open up new ways for substantial improvements in international reporting quality. At a national level, Ukraine requires the development of a modern system of forest accounting, which would aggregate national and management forest inventories, as well as forest monitoring, in a systems approach. State ownership of forests in the country would promote the development of such a system. Moreover, the increasing role of science in studying forest ecosystem services is urgently needed. For example, there are no eddy covariance measurements in Ukrainian forests, and remote sensing data are not used in the forest inventory in any systems approach.

The methods of carbon accounting used here are limited by an understanding of the processes occurring within forest ecosystems. Hence future research should include two important components in the account. One is the protective role of forests outside of forest areas, particularly in agroforestry landscapes, their impacts on the productivity of agricultural land, and the protection of soil and water. Second is a consideration of the impacts of technological chains of forest products from forests to end users and the impacts of these on emissions and removals of greenhouse gases.

Climate change generates substantial risks and challenges for Ukrainian forests. As has been shown in previous research, the vulnerability of Ukrainian forests to climate change is high even under moderate IPCC scenarios such as A1B (Shvidenko et al. 2017). According to this study, the central and southern regions of the country will face untenable conditions for the growth of forests by the end of this century with clearly negative consequences for the carbon budget of forest ecosystems. This would require substantial national efforts and strategies for the adaptation of forest ecosystems to climate change as well as mitigation efforts to tackle the undesirable consequences (Vasilchenko et al. 1998; Buksha and Pasternak 2005; Nijnik 2005; Shvidenko et al. 2017).

5 Conclusions

For countries that do not currently have land cover data with an accuracy of higher than 85%, e.g., Eastern European countries such as Russia, Belarus, and Moldova, the hybrid mapping methodology presented here provides an opportunity to develop forest maps that can be used in different national, regional, and global applications, including spatial-temporal accounting and verification of emissions and removals of greenhouse gases. This study shows that the application of advanced systems analyses to difficult and ill-defined tasks can result in outputs that are accurate enough to be used for policy implementation and forest management. The use of spatially explicit products such as those developed here minimizes the impacts of one of the most uncertain components of the carbon accounting of forest ecosystems, i.e., the lack of operational knowledge about spatial-temporal changes in forests, which is not satisfactorily reflected in the forest inventories of many countries.

However, with respect to further improvements in advanced methodologies for understanding the carbon cycle of forest ecosystems, this study presents an initial step forward in the development of a multi-sensor remote sensing approach. At the same time, this study highlighted information gaps in different areas, e.g., in understanding biogeochemical processes (particularly below ground) or in forest inventories. The study also underlined the need for better system consistency across all types of information inputs. Only a comprehensive integration of ground and remote sensing methods is able to satisfactorily cover the major requirements of a full and verified carbon accounting system. Further improvements in applications of remote sensing methods should deal with the estimation of the biophysical indicators of forest ecosystems, which are not defined satisfactorily (or are not currently defined at all) by current forest inventories. Among these, indicators of the vulnerability of forest ecosystems and the stability of forest landscapes are those of principal importance for the development of prospective national forest information systems in a world that is subject to ongoing environmental change.

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