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ANALYSIS OF METHODOLOGIES FOR CARBON STOCK ESTIMATION IN FORESTS

Abstract. Current approaches to carbon stock estimation in forest ecosystems are discussed. Datasets containing biomass and carbon stock estimates that can be used for training/validation in machine learning are described. Examples of applying the remote approach to assessing forest biomass over large areas are analyzed. To estimate the forest carbon stocks in Ukraine, the most promising is the remote approach, which combines ground-based and satellite measurements for forest classification and statistical modeling of carbon stocks. For training and validation of machine learning algorithms, it is proposed to use the GEDI Biomass Map covering most of the territory of Ukraine — from the southern borders to the latitude of Chernihiv in the north. A prototype of forest biomass estimating product in Ukraine can be based on publicly available MODIS NBAR data, SRTM DEM, ECMWF climate data and use the Random Forest machine learning method.
Keywords: forest, carbon stock, aboveground biomass, satellite data, GEDI, ICESat-2.

Problem statement. Global climate warming, caused by the anthropogenic increase of greenhouse gas concentration in the atmosphere, especially carbon dioxide (CO_2), has resulted in increased interest to assessing the carbon cycle in various ecosystems. The forest's significance in the carbon dioxide content regulation makes relevant the problem of forest carbon stock estimation.

The **objective** of the research is to choose a methodology for estimating carbon stocks in the forest ecosystems of Ukraine. For this, it is necessary to consider methods of forest biomass and carbon stock estimating, determine available data that can be used in stock assessment, and analyze approaches to solving such tasks and problems that arise in their implementation.

Carbon pools and flows. Nowadays' methodologies for estimating forest ecosystem carbon stock are based on instructions of the Intergovernmental Panel on Climate Change, IPCC [1]. According to [1], all the forest organic matter flows form four carbon pools (Fig. 1):

- aboveground biomass (AGB), and belowground biomass (BGB);

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- woody debris;
- litters;
- soil organic matter.

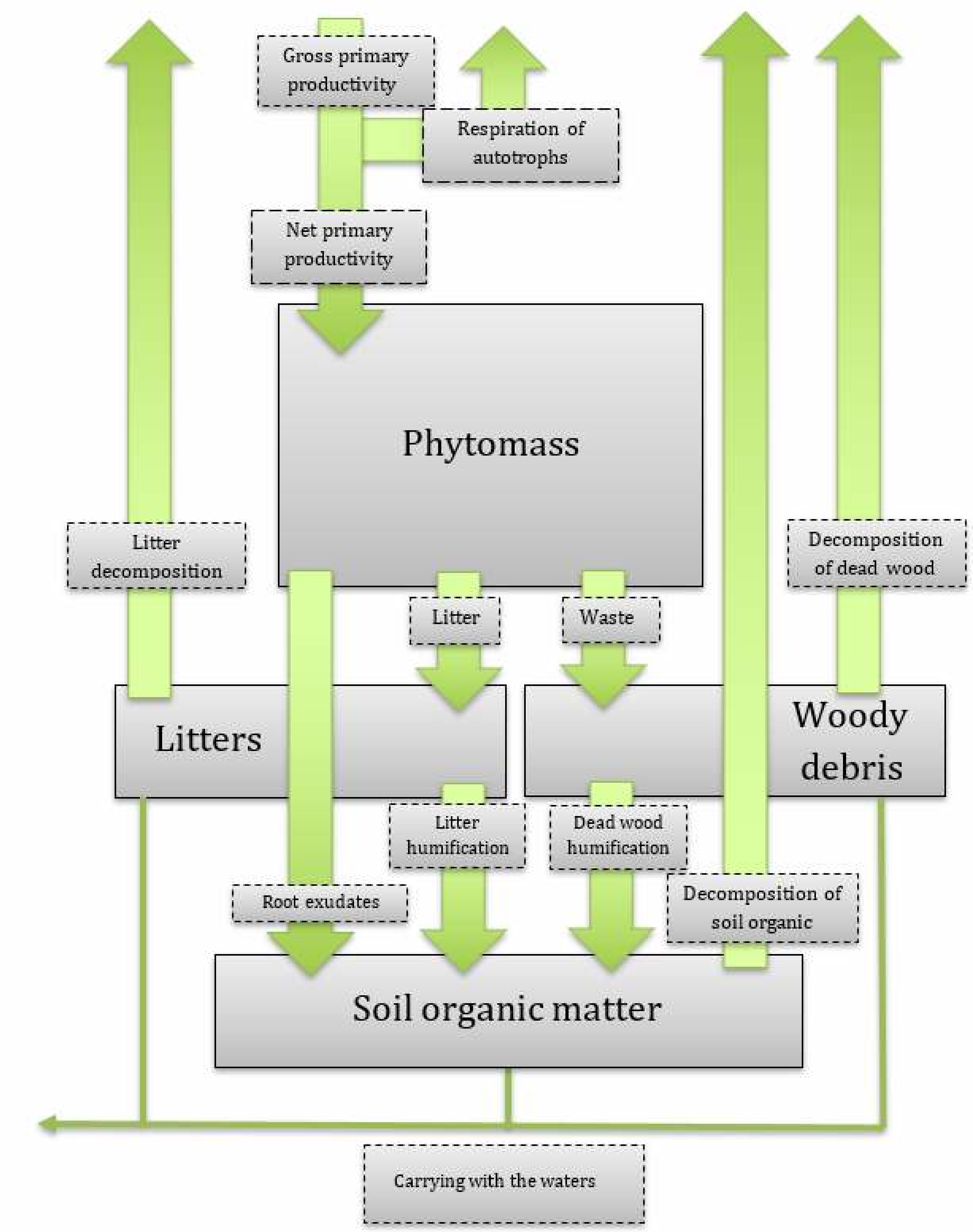

Figure 1 – Carbon pools and flows in forest ecosystems

If carbon pools increase in size, a CO_2 flow is created from the atmosphere; if the pools decrease, the greenhouse gas sources are formed.

During photosynthesis, atmospheric carbon dioxide is converted into organic matter. The total amount of organic matter formed during photosynthesis is called Gross Primary Productivity (GPP).

Part of this substance is decomposed during the plants' metabolism, while carbon dioxide is released into the atmosphere. This flow is called autotrophic respiration (Ra) and is estimated at 40–70% of GPP.

The difference between GPP and Ra characterizes the amount of organic matter replenishing the biomass pool and is called Net Primary Productivity (NPP). NPP can be determined in the field using weighting methods.

From the climate agreements follow the principles that should be taken into account when developing methods for assessing carbon [2]:

1. Of primary interest is the forest interaction with the atmosphere. That is, from all the flows, only the flows connecting forest carbon pools with the atmosphere are considered.

2. Sinks and sources of greenhouse gases in forests are subject to accounting and management, while the forest carbon stocks at the initial moment of management are not of particular significance.

3. Only sinks and sources of greenhouse gases resulted from human activities should be taken into account.

The carbon flows associated with each of the pools form the balance value determining the direction of pool change. The final estimate of the forest carbon balance can be obtained having determined the losses and subtracted them from carbon gains (Fig. 2). This approach called the flow balance method is recommended for use by the IPCC [1].

The carbon balance by biomass is most obvious. The young forest grows, its biomass, and hence carbon stocks, increase. A similar situation is observed for other carbon pools.

In old-growth forests, incoming and outward carbon flows usually balance out. The forest becomes carbon neutral with the atmosphere. The flow balance is the basis for the stable existence of an old-growth forest ecosystem. The fact that even in the case of a high photosynthetic runoff, old-growth forest is neutral in terms of carbon balance with the atmosphere, underlies most systems for regional assessment of forest carbon budget [2].

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Thus, young forests have carbon increments in different pools, while in old-growth forests pools are stable. If the information on the forest's age structure and typical growth rates is available, it is possible to estimate the total pool increments in each region.

The second method recommended by IPCC — by stock difference — is used with consecutive information on carbon pools in forests. The annual carbon balance estimate is the stock difference between consecutive counts, referred to the interval duration between observations.

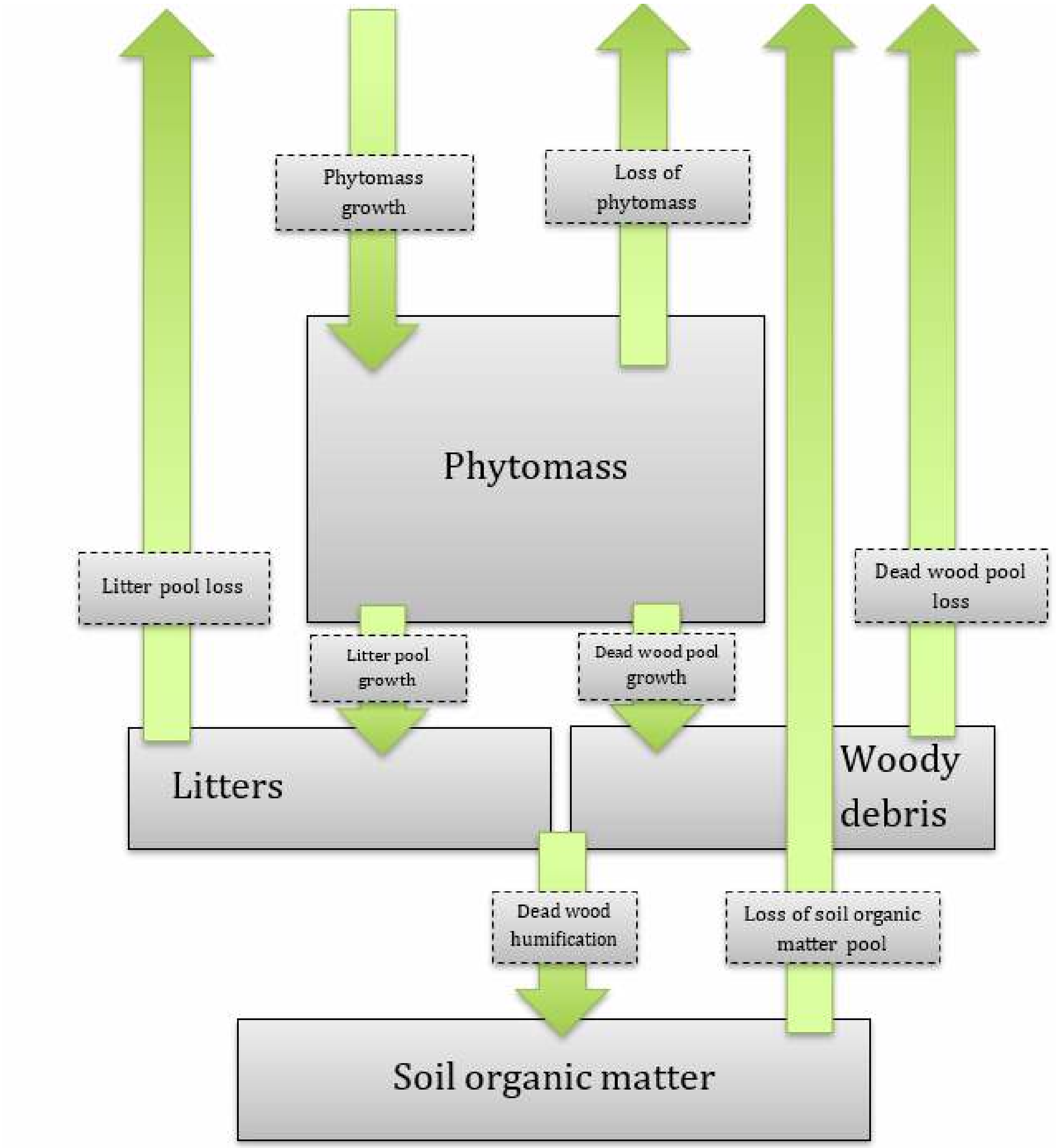

Figure 2 – Forest carbon budget flowchart

Approaches to carbon stocks estimation. Let's consider approaches to estimation carbon stocks, paying special attention to the use of remote sensing satellite data in these approaches. There are currently four basic approaches to a regional assessment of forest carbon stocks:

- cartographic;
- conversion;
- remote;
- model.

In the cartographic approach, forest polygons are first identified. Correspondences are then established between polygons and typical values of carbon stocks, which are calculated from local databases. The sum of polygon areas products by typical values gives the carbon stock estimate for study area [2]. Some countries have developed models based on variables describing forest plantations, such as tree species, plot indices, ecological regions, etc. [4]. Optical satellite data are actively used to classify forest plantations, and to identify homogeneous forest polygons. Cartographic models are the simplest among the models for estimating carbon stocks, providing relatively rough estimates [2]. Examples of using the cartographic approach are given in [8, 9]. Models that implement the cartographic approach are spatial stepwise regression based on expert estimates.

The conversion approach is applied to forest ecosystems and areas for which forest inventory information is available. This information includes volume wood stocks necessary for the economic assessment of forest resources. Volume wood stocks are converted to mass of organic matter or carbon using conversion factors. Such a conversion has a clear physical justification: volume is related to mass through density. The conversion factor allows estimating the stem wood carbon. Other biomass fractions (roots, branches, leaves) are functionally related to the trunk mass and are also included in the calculation of conversion coefficients [2]. Equations relating the biomass stock to the taxation characteristics of trees (height, trunk diameter, etc.) are called allometric equations. The most time-consuming part of the work is forest inventory, for which aircraft-based lidars are actively used. In addition, the allometric equations with selected coefficients should be used for each tree species. These equations are usually local, that is, they provide a good stock estimate only within a particular ecological region. A conversion approach to estimating forest biomass carbon stocks is recommended by the IPCC guideline [1]. However, it is very costly and labor-intensive. Optical satellite data (usually of high spa-

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tial resolution) can be used to classify forests. The conversion approach models are power-law regressions on ground-based data.

The remote approach is a regression between predictors generated from satellite (optical and radar) and other data, trained on samples obtained during ground-based measurements (that is, as a result of the spot use of conversion approaches). In contrast to the cartographic approach, satellite data are used both for the homogeneous areas' allocation (classification or segmentation) and for regression in each pixel of the study area. The remote approach is less labor-intensive than the conversion approach since it requires less ground-based data. The training data sources for this approach will be discussed in the next section. An important feature of remote approach is the ability to generate time series of AGB maps, as it relies to a large extent on regular satellite observations rather than sparse forest inventory data.

The modeling approach, on the one hand, is a combination of cartographic and conversion approaches. That is, the model is either applied to polygons or pixels of digital maps or uses information from forest inventories on volumetric wood stocks [2]. On the other hand, modeling approaches include deterministic mathematical models that allow not only to estimate but also forecast carbon stocks and flows. Modeling approaches are focused on considering a detailed scheme of the carbon cycle (for example, they take into account the transition of forest plantations from one age stratum to another over time), followed by an estimation of carbon losses due to forest cover disturbance. Satellite data in modeling approaches are used to generate digital maps. Examples of carbon stock estimation models: IIASA [2, 10], ROBUL [11], CBM-CFS3 [12]. All of them are complex mathematical models, having been developed and verified for 10 to 20 years, requiring a large amount of ground-based data.

Biomass maps and carbon stocks. The current projects aimed at creating continental and global biomass maps: NASA GEDI product at 1 km resolution (2020, 2021), NASA ICESat-2 product for the northern polar latitudes (30 m resolution, 2020), NCEO for Africa at 100 m resolution (2017), CCI-Biomass global product at 100 m resolution (2010, 2017, 2018, 2020), JPL product at 100 m resolution (2020).

GEDI Biomass Map. Dataset at 1x1 km resolution consisting of two raster files: aboveground biomass density (ABGD) and mean aboveground biomass density standard error ($Mg{\cdot}ha^{-1}$) (Fig. 3, Fig. 4). GEDI Biomass Map data cover the territory of Ukraine from the south up to the Chernihiv latitude. Higher latitudes are not available to the GEDI lidar aboard the International Space Station.

- Spatial Resolution: 1 km

- Spatial Coverage: global within a nominal latitude extent of 51.6°N to 51.6°S
- Temporal Coverage: 2019-04-18 — 2021-06-09
- Update Frequency: annual
- Format: GeoTIFF
- Access: GEDI L4B Gridded Aboveground Biomass Density, Version 2
- User Guide:

https://daac.ornl.gov/GEDI/guides/GEDI_L4B_Gridded_Biomass.html

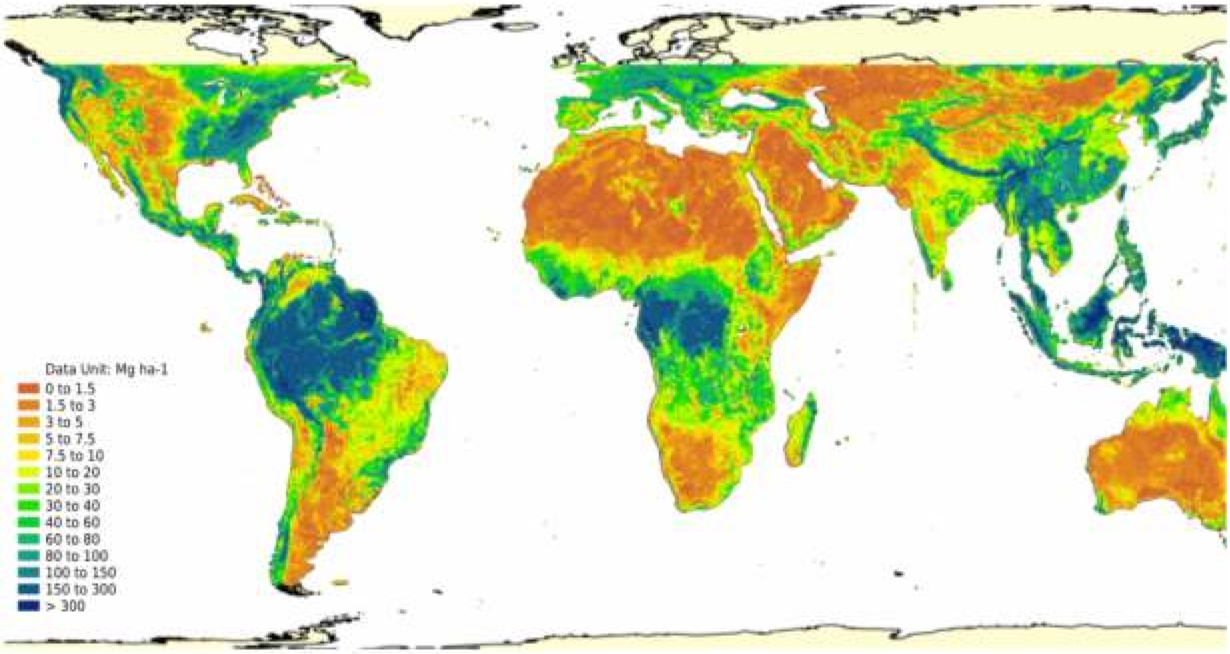

Figure 3 – GEDI L4B Gridded Mean Aboveground Biomass Density (webmap.ornl.gov)

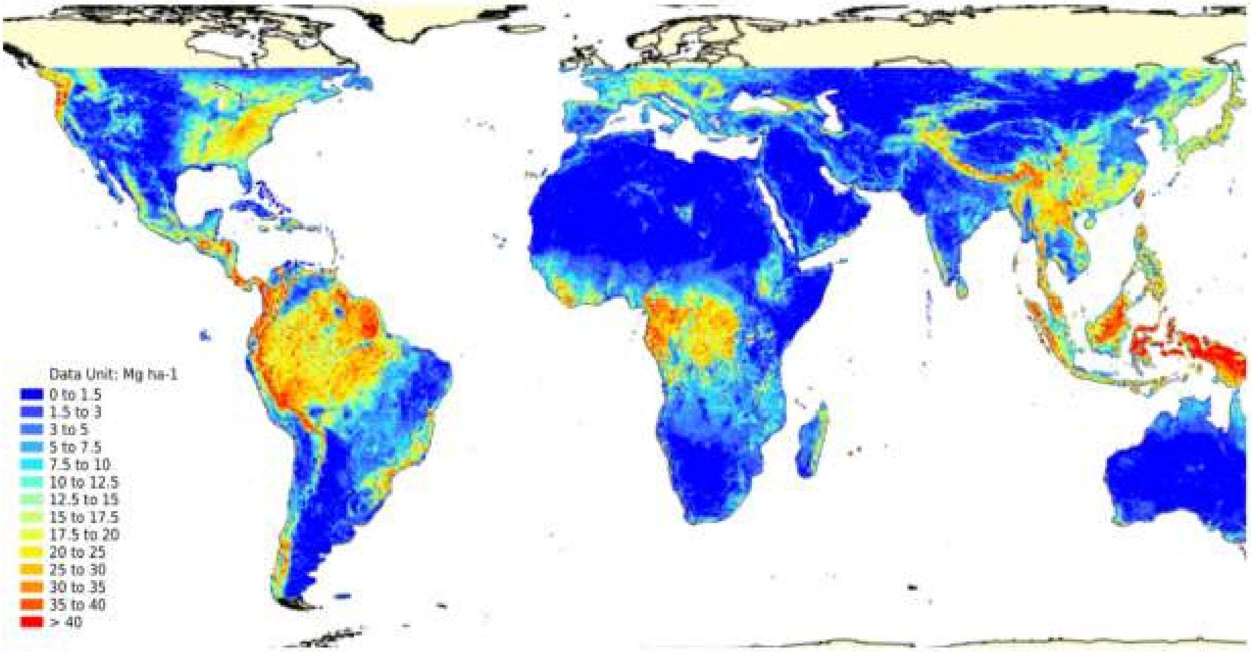

Figure 4 – GEDI L4B Gridded AGBD Standard Error (webmap.ornl.gov)

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The AGBD value refers to the whole pixel. To calculate AGBD for the pixel area covered with forest, AGBD should be partitioned by the fraction of this area.

ICESat-2 Boreal Biomass 2020 Map. The ICESat-2 Boreal Biomass Map for 2020 provides boreal-wide woody aboveground biomass density values (ATL08), filling a gap in the GEDI data. The data were obtained using the Advanced Topographic Laser Altimeter System (ATLAS) lidar on the ICESat-2 satellite.

- Spatial Resolution: 30 m
- Spatial Coverage: 50° N — 75° N
- Temporal Coverage: 2020
- Update Frequency: annual
- Format: HDF5
- Data access and user manual (ATLAS/ICESat-2 L3A Land and Vegetation Height, Version 5): https://nsidc.org/data/ATL08

NCEO Africa Aboveground Woody Biomass 2017. NCEO Africa Aboveground Woody Biomass (AGB) map for the year 2017 at 100 m spatial resolution. The dataset consists of two files: the Aboveground Woody Biomass Raster and the Biomass Estimation Uncertainty Characteristics Raster at a 100 m resolution. AGB is dry matter in $Mg{\cdot}ha^{-1}$. A map is a continental-scale dataset combining different-type data. First, a Canopy Height Model (CHM) map was created by combining tree canopy height measurements from GEDI lidar and ALOS-2 PALSAR-2 L-band radar for a forest mask generated from Landsat-8 data. An empirical model relating CHM with AGB was then used to estimate AGB, trained on data from several airborne lidars. Therefore, the accuracy of biomass estimates may vary for different regions and vegetation types.

- Spatial Resolution: ~100 м.
- Spatial Coverage: Africa
- Temporal Coverage: 2017
- Update Frequency: annual
- Format: GeoTIFF
- Access: https://doi.org/10.25392/leicester.data.15060270.v1
- User manual:

https://leicester.figshare.com/articles/dataset/Africa_Aboveground_Biomass_map_for_2017/15060270/1?file=28962087

CCI BIOMASS provides AGB maps for four observation periods (epochs) and the standard deviations of the corresponding AGB estimates. The AGB product consists of global datasets with AGB estimates ($Mg{\cdot}ha^{-1}$). AGB is a dry weight of the woody parts (trunk, bark, branches, and shoots) of all living trees, excluding stumps and roots.

- Spatial Resolution: ~100 m at the equator
- Spatial Coverage: global
- Temporal Coverage: 2010, 2017, 2018, and 2020
- Format: NetCDF, GeoTIFF
- Access: https://climate.esa.int/en/odp/#/project/biomass (data for 2010, 2017, and 2018 available as of 30.04.2022)
- User manual: https://climate.esa.int/media/documents/D4.3_CCI_PUG_V3.0_20210707.pdf

JPL 2020 Global Biomass Dataset. The JPL 2020 map is a global estimate of AGB density in $Mg \cdot ha^{-1}$ based on a combination of Landsat-8, ALOS-2 PALSAR-2 (2019-2020), and SRTM DTM composite data at a spatial resolution of 100 m. The boosting tree machine regression model was trained on ICESAT-1 space lidar data samples, airborne lidar data, and field inventory data.

- Spatial Resolution: ~100 m
- Spatial Coverage: global
- Temporal Coverage: 2020
- Update Frequency: annual
- Format: GeoTIFF
- Information about data: https://ceos.org/gst/jpl-biomass.html (as of April 30, 2022, there are no open access data)

The product is supposed to be placed on the Multi-Mission Algorithm and Analysis Platform (https://ops.maap-project.org/search/), divided by continents (Africa, Asia, Europe, North and South America, Oceania).

Biomass Estimation Challenges. Long-term practice of using allometric equations relating physical characteristics of trees (height, trunk diameter, etc.) with biomass has proved the effectiveness of these models. Nowadays they provide the most accurate biomass estimates compared to other indirect methods and are recommended by the IPCC [1]. However, like all models, biomass estimates using allometric equations contain an error of about 15–20% for tropics [7]. This is the price of transition from direct biomass measurement through cutting down trees and burning wood to estimating biomass with a model.

An important peculiarity of allometric models is their locality. Models vary depending on climatic conditions, vegetation structure, tree species, and forms of their growth. Different forest biomes (tundra, taiga, broad-leaved forests, etc.) and even

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individual regions within a biome are described by different allometric models. Model transfer from one region to another (even for one tree species) requires at least careful justification, and the creation of a new model requires long-term and expensive ground-based observations. When using different allometric models in one area, the differences in carbon stock estimations reached 93% [4]. Thus, it is possible to rely on allometric models only in those regions and for those tree species for which these models are adapted. To expand the scope, other approaches to assessing biomass should be used, in particular, remote.

Despite the wide use of optical remote sensing data, their ability to assess AGB in forests is limited due to poor penetration under the forest canopy, cloudiness, and saturation [3, 4]. Saturation is expressed in the fact that, upon reaching a certain forest biomass density, the image characteristics (for example, spectral reflectivity or vegetation indices) become not sensitive to biomass changes [3]. It seems obvious that an increase in the spatial resolution of optical data should reduce the influence of the saturation effect. However, estimates relating saturation to a spatial resolution of the data could not be found in the literature. At the same time, several publications [3, 5] indicate that the use of multispectral optical data (Landsat, MODIS) makes it possible to provide an acceptable quality of AGB estimates.

The possibilities of radar signal penetration under the forest canopy depend on the range: X-band and C-band signals practically do not penetrate under the forest canopy, while L- band and P-band signals penetrate there freely. However, satellite radars of all bands are used to monitor forests. Despite the positive correlation of reflected radar signal with forest structure parameters, there is also a saturation problem for radar data. Saturation can occur in different types of temperate, boreal, and tropical forests. It depends on wavelength, polarization, vegetation characteristics, and soil conditions. It is noted in [3] that the saturation effect is present even for L-band signals. In addition, it is difficult to estimate AGB from SAR data alone since these data provide information on the surface roughness and do not distinguish between vegetation types [3].

A breakthrough in forest surveillance is expected from the launch of ESA BIOMASS (scheduled for 2023), a P-band (70 cm wavelength) satellite radar. BIOMASS is expected to significantly increase the accuracy of AGB estimation (reduce the standard error to ±10 $Mg \cdot ha^{-1}$ for AGB below 50 $Mg \cdot ha^{-1}$ and the relative error to ±20% for AGB above 50 $Mg \cdot ha^{-1}$). However, the BIOMASS mission is limited to measurements outside the US Space Objects Tracking Radar range. This means that the sensor will have to be disabled in North and Central America, as well as in

Europe. However, most biomass-rich tropical forests will be covered by BIOMASS observations.

Lidars are the best in terms of biomass estimation capabilities [3, 4, 6]. In recent years, aviation lidars have become an indispensable tool for forest inventory. There are currently two satellite lidars in orbit: GEDI and ICESat-2. They provide spot estimates of biomass that can be used to train regression models generated from other remote sensing data.

AGB mapping is a priority for several current (GEDI, ICESat-2) and advanced (BIOMASS, ALOS-4, and NISAR) space missions. Although new satellite products for AGB estimation are a positive trend, the simultaneous existence of a large number of such products without their consistent and transparent intercomparison/validation threatens the successful use of any of them for biomass estimation. Currently, several large organizations such as NASA, ESA, CEOS, JAXA, etc. are developing a single consistent product for biomass estimation based on existing products (scheduled for release in 2022) [6]. The Multi-Mission Algorithm and Analysis Platform (MAAP) online platform (https://earthdata.nasa.gov/maap-biomass/) – a joint project of NASA and ESA was created to provide the product access.

Examples of using the remote approach to biomass estimation. In [13, 14], maps of carbon stocks in the tropics were generated using data from ground-based measurements, the Geoscience Laser Altimeter System (GLAS) lidar of the ICESat satellite, the earth's surface spectral reflectivity, and temperature, measured by the MODIS spectrometer onboard Terra and Aqua satellites, as well as a digital elevation model (DEM) SRTM (in [14], the QSCAT scatterometer data were also used). The mapping approach [13, 14] was used for many subsequent studies. Let's consider it using the example [13]. This work was implemented in three stages: 1) ground samples collection, 2) ground sample expansion using satellite lidar data, and 3) regression on the generated sample.

In the first stage, a protocol was developed to standardize data collection and ground-based measurements were carried out (2008–2010) in the GLAS lidar coverage area, in a wide range of climatic conditions — in tropical Africa, America, and Asia. Measurements of aboveground biomass characteristics taken at the center of the GLAS footprints (circle 70 m in diameter) were included in the number of samples.

Enlarging of the training sample. In the second stage, the density of tree biomass was estimated from field measurements using allometric equations. Tree biomass density was converted to carbon using a 0.5 factor. A statistical relationship (regres-

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sion) between the biomass estimates from ground-based measurements and the lidar waveform metrics was determined. This allowed field measurements to be extended to thousands of new locations (GLAS footprints). The allometric equations were selected individually for each vegetation class at ground measurement points (there are more than 10 such classes in [13]). It should be noted that in [13] the study area was not zoned, and a single relationship was used for the regression between the lidar signal metrics and carbon stocks (global linear regression). As a result, the expanded sample contained more than 5 million elements.

Spectral reflectivity, ground temperature, and DEM as features. In the third stage, the obtained sample was used to train the model, in which the MODIS Nadir BRDF-Adjusted Reflectance (NBAR), MODIS Land Surface Temperature (LST), and SRTM DEM data were used as predictors. Among the predictors, the MODIS Red (B1, 620–670 nm) and SWIR (B7, 2105–2155 nm) bands proved to be the most important variables for explaining the dispersion of aboveground carbon density.

Random Forest. The Random Forest machine learning algorithm was used to generate the model. This method is used in many works on biomass estimation as a simple and reliable non-linear regression method.

Zoning. In [15], clustering is used to create a training sample: the study area is divided into segments, in which the required number of samples is selected (ground-based biomass estimates). Then the classification trained on these samples was used. Biomass was modeled from optical indices.

Textural features. Asner et al. [16] combined Landsat predictors with variables based on the SRTM DTM to map carbon stocks in Peru. Grey-Level Co-occurrence Matrix (GLCM) and Fourier Transform Textural Ordination (FTTO) metrics were used as surface texture features. Measurements from aviation lidar were used for training. Regression was based on Random Forest method.

Climatic features. In [17], four climatic parameters — Mean Annual Precipitation (mm), Mean Annual Temperature (°C), Mean Relative Humidity (%), and Mean Annual Evaporation (mm) — are modeled based on the dependence on the height gradient (data from neighboring weather stations were used for training). These climate parameters, along with the 5 spectral vegetation indices (RVI, NDVI, SR, NDGI, DVI, and TVI) and near-infrared (NIR) spectral reflectance, extracted from SPOT-6 satellite data, were then used to model carbon stocks in the forests of northern Iran. The training was based on ground measurements. Modeling method: multivariate linear regression. Precipitation and temperature influenced the carbon stock estimates most of all among climatic parameters. NDVI and RVI indices as well as spectral reflectance in the NIR band influenced the most among satellite data.

The use of boosting (CatBoost). In [18], predictors and machine learning methods with the least mean squared error (RMSE) of carbon stocks determining were analyzed. Totally 53 predictors were investigated: 6 Landsat OLI spectral bands, 11 vegetation indices, textural features (GLCM) — 8 features for four window sizes (3x3, 5x5, 7x7, and 9x9). Terrain features: elevation, slope, and aspect (SRTM), as well as canopy density. Among the algorithms, CatBoost proved to be the best, overtaking XGBoost and Random Forest.

Models for each forest type. To improve the accuracy of carbon stock estimates, 5 models were used in [19] for the following forest types: Evergreen Needleleaf Forest, Evergreen Broadleaf Forest, Deciduous Needleleaf Forest, Deciduous Broadleaved Forest, and Mixed Forests.

Biophysical predictors. A combination of lidar data, optical satellite sensors, and ground-based measurements [19] was used as predictors for estimating AGB forest stocks: biophysical predictors (high-level products in [19]) LAI, GPP, VCF (Vegetation Continuous Fields), and Land Cover (MODIS data), canopy height (ICEsat), climatic variables (monthly mean temperature, total precipitation data) and DTM SRTM. Regression method: a gradient boosting regression tree. The validation results demonstrated good accuracy with $R^2 = 0.90$ and a standard error of 35.87 $Mg{\cdot}ha^{-1}$.

Backscatter inversion. In [20], the BIOMASAR algorithm was proposed for estimating AGB from satellite radar data. The algorithm consists of two main steps:

1. creation of a stack of calibrated, geocoded, and co-registered radar images (containing backscatter coefficient values);

2. inversion of individual backscatter measurements with a Water Cloud type model for estimating growing stock volume (GSV) and a multi-temporal combination of individual GSV estimates.

The modern version of BIOMASAR, which uses multi-temporal ALOS-2/PALSAR-2 L-band radar data, is discussed in [21].

Multi-sensor data. The use of combinations of optical and lidar data as well as radar and lidar data naturally leads to the idea of combining all three data types to improve the AGB estimate accuracy. This approach was proposed in [22], where multiseasonal Landsat images were used to obtain information on the forest species composition in the study area, aviation lidar data to measure the forest canopy height, texture metrics, as well as Sentinel-1 radar data. The regression is based on

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the Random Forest method and uses USFS ground inventory and forest analysis data for training and validation. The best model reached $R^2 = 0.625$, with a RMSE = 18.8 $Mg{\cdot}ha^{-1}$ (47.6%) at a spatial resolution of 30×30 m. The five most influential features are the 95th, 85th, 75th, and 50th percentiles of point height measured by lidar and the standard deviations of the 85th percentile of height.

The CCI Biomass and JPL 2020 Global Biomass datasets mentioned above are also examples of regression applications for various satellite data, and the description of algorithms for constructing these datasets (not published as of 2020-05-02) should be studied in more detail.

Conclusions. Existing approaches to carbon stocks assessment in forest ecosystems are considered. The most preferable for practical use over large areas is the remote approach, which combines ground-based and satellite measurements for forest classification and carbon stock regression.

Datasets with biomass and carbon stock estimates are described that can be used to train and validate machine learning methods. The most promising product for Ukraine is GEDI Biomass Map, covering most of the territory of Ukraine — from the southern borders to the latitude of Chernihiv in the north.

Examples of remote approach applications to forest biomass estimation are discussed. Promising predictors and machine learning methods are indicated. An analysis of examples showed the importance of preliminary partitioning of a large study area into zones. Such partitioning, as well as the search for predictors and machine learning methods, will require additional research.

A prototype product for estimating forest biomass in Ukraine can be based on publicly available MODIS NBAR data (MCD43A4), SRTM DEM, ECMWF climate data, and can be used to train the GEDI Biomass Map model. As test regions, it is proposed to use 3-5 regions of Ukraine with different natural conditions and forest types.

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Аналіз методик оцінки запасів вуглецю у лісах

Розглянуто сучасні підходи до оцінки запасів вуглецю у лісових екосистемах. Існує чотири базові підходи проведення регіональної оцінки запасів вуглецю в лісах: картографічний; конверсійний; дистанційний; модельний. Найбільш перспективним для практичного використання на великих територіях є дистанційний підхід, що поєднує наземні та супутникові вимірювання. На відміну від картографічного підходу, супутникові дані використовуються для класифікації лісів та регресії запасів вуглецю у кожному пікселі досліджуваної області. Дистанційний підхід менш трудомісткий, ніж конверсійний, оскільки потребує менших обсягів наземних даних. Важливою особливістю дистанційного підходу є можливість створювати за його допомогою тимчасові ряди карт AGB.

Описано набори даних, що містять оцінки біомаси та запасів вуглецю, які можна використовувати для навчання/валідації у машинному навчанні. Розглянуто та проаналізовано приклади застосування дистанційного підходу до оцінки біомаси лісу, визначено перспективні предиктори. Аналіз прикладів показав важливість попереднього розбиття (у разі великої площі) області дослідження на відповідні зони.

Для оцінки запасів вуглецю лісів України найбільш перспективним є дистанційний підхід, що поєднує наземні та супутникові вимірювання для класифікації лісів та статистичного моделювання запасів вуглецю. Для навчання та валідації алгоритмів машинного навчання пропонується використовувати GEDI Biomass Map, що покриває більшу частину території України — від південних границь до широти Чернігова на півночі. Прототип продукту для оцінки біомаси лісів України може спиратися на загальнодоступні дані MODIS NBAR, ЦМР SRTM, кліматичні дані ECMWF та використовувати метод машинного навчання Random Forest.

Ключові слова: ліс, запас вуглецю, наземна біомаса, супутникові дані, GEDI, ICESat-2.

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