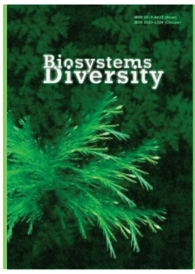

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Aboveground biomass estimation in conifer and deciduous forests with the use of a combined approach

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The complex action of environmental factors often triggers the biomass formation in forest plantations, which is crucial for carbon balance and environmental monitoring, especially in the context of climate change. In this article, we present data on the aboveground biomass accumulation for black locust and common pine (*Pinus sylvestris* and *Robinia pseudoacacia*) as the two most common forest-forming species in the steppe zone. For this purpose, we propose a reliable approach to monitoring of aboveground forest biomass with combining Sentinel-2 multispectral imaging techniques (with L-band) and biometric processing data from coniferous and deciduous stands obtained from field surveys. We represent the results of field surveys with established indicators of aboveground biomass of forest plantations in the field experiment, which averaged 159.9 ± 9.0 t/ha in the studied region. The biometric indexes obtained from the field experiments were used to develop models for predicting biomass using the remote method. Based on the processing of satellite image data, forest vegetation indices were analysed, among which the NDVI (normalized difference vegetation index) was the best predictor to assess biomass. The multiple regression method was found to be the best for predicting and mapping the aboveground biomass in *P. sylvestris* and *R. pseudoacacia* within the studied area (RMSE – 23.46 t/ha). Based on the results obtained, we created a map of the aboveground biomass distribution in black locust and common pine stands within the studied region. We established reliable correlations between biometric parameters (mean diameter at breast height, mean height) and aboveground biomass of stands with indicators of spectral bands in satellite images. This enables us to use the constructed models to estimate the overall productivity of coniferous and deciduous forest stands for large areas.

Keywords: biomass; NDVI; multispectral images; *Pinus sylvestris*; *Robinia pseudoacacia*; multiple regression method.

Introduction

Determination of plant biomass combines the methods with the use of allometric assessment in field condition and remote sensing approach. Estimation of aboveground biomass with biometric measurements generally has the advantages of good to excellent accuracy (Bolyn et al., 2018; Luo et al., 2020; Zhang et al., 2022). But obtaining information for a large area is impossible in this case, while real-time monitoring is disabling. Recently, the combination of the methodology of assessing vegetation biomass using aboveground data and modelling of the obtained indicators is considered to be the most promising research method. The models then can be used to calculate the same indicators and handle them using satellite imagery.

The first moderate-resolution earth surface observations under the Landsat program were performed with the Landsat 1 satellite that was launched in 1972 (Markham et al., 2012). A detailed description of the satellite types and their historical development was presented by Li et al. (2020). Most of these satellites can be used to assess inorganic elements in soils and vegetative parts of plant communities. Early studies on biomass assessment using Landsat were carried out in structurally simple temperate and boreal forests. As early as that time, vegetation indices were the most commonly used approach in optical remote sensing for estimating biomass (Ahamed et al., 2011; Demol et al., 2022). Calculations of most vegetation indices are based on the relationship between red and near-infrared wavelengths. This maximizes the spectral contribution of green vegetation and minimizes the influence of soil, sun angle, etc. (Guerra-Hernández et al., 2022).

However, to date, no remote sensing satellite has provided direct measurements, estimates, and mapping of aboveground forest biomass (AGB) (Le Toan et al., 2011; Quegan et al., 2019), though the National Aeronautics and Space Administration (NASA) (GEDI) Global Ecosystem Dynamics Study aims to monitor ecosystem dynamics and fluctuations in carbon fluxes around the world (Dorado-Roda et al., 2021). In most studies, biomass values measured in field surveys are used to develop models for predicting AGB values by linking biophysical parameters obtained from remote sensing data (Abbas et al., 2020; Lovynska et al., 2024). Most of the coarse and medium spatial resolution datasets, such as MODIS, Landsat, and ASTER, provide the potential to estimate AGB at various scales (from subnational to national, regional, and global levels) (Brandýsová & Bucha, 2013). At the same time, the application of mixed pixels and coarse or medium spatial resolution data is problematic for estimating aboveground biomass, and the estimated areas have a complex environment with mixed tree species in forest canopy (Lu, 2006). That is why it is better to use high-resolution satellite data for evaluation and mapping.

At the local or subnational level, high-resolution satellite data can provide better results in mapping of aboveground biomass (Hussin et al., 2014).

The issue of vegetation assessment (mainly in forests) and aboveground biomass restoration is quite well solved with remotely sensed data. A number of methods are known for this purpose:

– empirical, physical, and mechanical modelling based on spectral indices and X, C or L bands radar data (Tian et al., 2023), as well as on data from airborne lidar (Ferraz et al., 2016), and terrestrial lidar (Demol et al., 2022);

– linear regression (Jos et al., 2021), multiple linear regression (Nuthammachot et al., 2018), nonlinear regression (Piestova, 2015; Naik et al., 2021) with satellite and airborne measurements, including lidar (Zaki et al., 2016) and multipolarization radar data (Huang et al., 2018; Zaitseva et al., 2021);

– advanced machine learning techniques such as support vector machine (SVM), random forests (RF), gradient boosting (GB), and Bayesian regularization network (BRN) (Huang et al., 2023);

– deep learning methods have recently been widely used (Schreiber et al., 2022; Pascarella et al., 2023).

The aboveground biomass of Scots pine and black locust has been extensively studied worldwide where these species are spread (Shupranova et al., 2022). Along with the common oak, these two tree species are still among the most common forest-forming species in the Steppe zone, in particular, within Dnipropetrovsk region. There are only few studies devoted to estimating the aboveground biomass of the above-mentioned species for a given region, especially using remote sensing techniques (Lovynska et al., 2021).

In this article, we have reviewed remote sensing methods based on the use of field analysis with aboveground biomass determi-nation. The article focuses on a comprehensive assessment of the biomass in forest stands, with the possibility of implementing the obtained developments at the national and global levels. The aim of the work was to assess the aboveground biomass of forest stands formed by Scots pine and black locust using a combination of field and remote methods.

Materials and method

Study area. The study area is located in artificial Scots pine and black locust stands in different parts of Dnipropetrovsk region (47–49 °N; 33–37 °E), Ukraine (Fig. 1). In this area of Steppe zone, the climate is temperate continental with mild winters. In Dnipro region, the amount of snow is small enough but summer usually is hot and dry with frequent downpours and strong southern winds. Average annual temperature is 10.6 °C, and annual total precipitation is 400–490 mm (Gulchak et al., 2011; Pakhomov et al., 2019; Shupranova et al., 2019; Holoborodko et al., 2021).

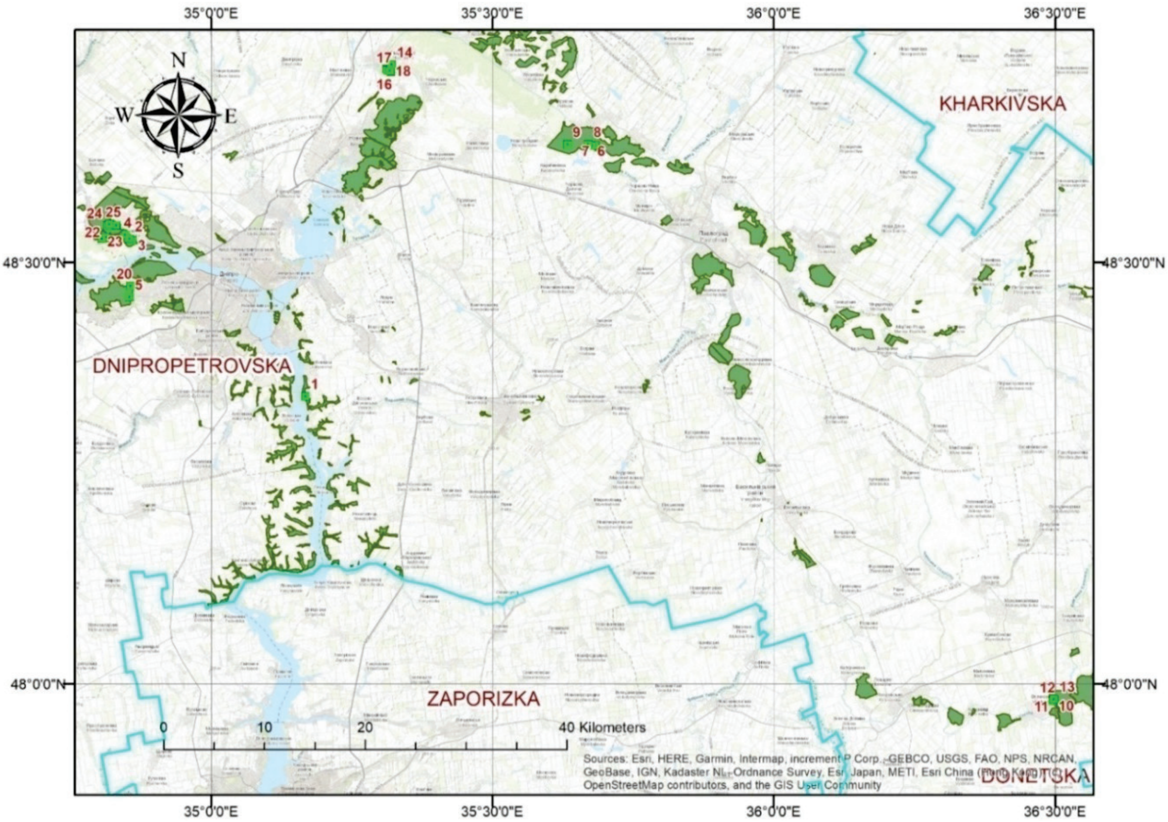

Fig. 1. Geographic extent of the study area within Ukraine (right up corner) and the map of the forest distribution in Dnipropetrovsk region with indicated temporally sample plots

Assessment of aboveground biomass of forest plantings in field surveys. The study was divided into two stages: field and laboratory conducted during 2016–2022. During the assessment of above-ground biomass, we used convenient methods of forest taxation in the study. The areas of studied temporary sample plots (TSP) were laid in stands of Scots pine and black locust in Dnipro region within the Northern Steppe zone of Ukraine. The selection of representative forest sites was carried out in accordance with the methodology developed by Lakyda (2002). We conducted the field surveys in the summer at 40 sites based on the random sampling method (Table 1). TSPs with investigated forest-forming species (Scots pine and black locust) had sizes from 0.11 to 0.50 ha and the stands' relative density varied in the range of 0.41–0.97 (Table 1).

The investigated TSPs were located in 6 enterprises within the responsibility of the State Agency of Forest Resources: Obuchivsky – 10 plots, Novokodazkuy – 3 plots, Pereschepunskuy – 3 plots, Vasilkovskiy – 10 plots, Verchnedneprovskiy – 6 plots, Novomoskovskiy – 8 plots. The size of each plot was 50 × 50 m. The forest stands in the test sites were artificial in their origin, differed in the types of forest-growth, microclimatic and edaphic conditions. Methodological features of determining the biomass of individual trees and stands of Scots pine and black locust by land method in the conditions of the Northern steppe are described in detail in our previous works (Lovynska et al., 2018; Sytnyk et al., 2018). We determined the mean diameter, height of stands, and aboveground biomass of forest plantings at the experimental plots. The mean diameter of plantings ranged from 20.7 to 29.1 cm, the height of stands from 19.7 to 22.4 m, and aboveground biomass from 190.4 to 372.3 t/ha (Table 2).

Table 1
Characteristics of temporary sample plots (n = 40) used in the field experiment on aboveground biomass estimation

No.	Longitude	Latitude	TSP area, ha	Relative density	Share of *P. sylvestris* in stand, %	Share of *R. pseudoacacia* in stand, %
1	35.167389	48.342110	0.30	0.94	99	–
2	34.854222	48.528430	0.20	0.65	100	–
3	34.859614	48.526470	0.20	0.88	19	56
4	34.847392	48.532980	0.12	0.68	94	2
5	34.854464	48.459720	0.11	0.96	80	20
6	35.676472	48.638190	0.25	0.68	100	–
7	35.682611	48.638530	0.25	0.69	100	–
8	35.669481	48.639440	0.25	0.50	100	–
9	35.632944	48.639580	0.25	0.61	100	–
10	36.495331	47.979610	0.25	0.48	100	–
11	36.498928	47.980690	0.25	0.49	100	–
12	36.496142	47.980790	0.25	0.64	100	–
13	36.497050	47.982190	0.25	0.52	100	–
14	35.319861	48.733210	0.25	0.57	94	–
15	35.311572	48.728130	0.20	0.62	99	–
16	35.313294	48.727430	0.25	0.41	71	–
17	35.312397	48.727060	0.25	0.59	96	–
18	35.316769	48.726280	0.25	0.44	83	–
19	35.319086	48.725300	0.25	0.74	100	–
20	34.831289	48.543790	0.20	0.94	96	4
21	34.268214	48.683355	0.16	0.56	–	96
22	34.157935	48.601896	0.25	0.88	–	100
23	34.301818	48.576827	0.20	0.63	23	47
24	34.810506	48.549710	0.40	0.94	–	100
25	34.882752	48.551487	0.25	0.65	58	22
26	34.811727	48.463877	0.50	0.73	–	100
27	35.255684	48.235826	0.49	0.82	–	100
28	35.171605	48.385719	0.25	0.81	–	94
29	35.375852	48.779874	0.50	0.71	–	100
30	35.481280	48.762827	0.25	0.85	–	95
31	35.168827	48.259421	0.25	0.78	–	100
32	35.114996	48.318306	0.29	0.91	–	100
33	33.384473	47.966465	0.18	0.97	–	100
34	33.317399	47.517307	0.25	0.77	6	96
35	36.571884	48.014880	0.25	0.71	3	97
36	36.707130	48.092811	0.25	0.88	–	100
37	34.226736	47.730595	0.25	0.82	–	100
38	36.141024	48.440580	0.25	0.72	–	100
39	36.359748	48.463647	0.25	0.58	–	100
40	34.562085	48.640617	0.25	0.67	–	100

Table 2
Biometric measurements of trees within Scots pine and black locust plantations

Location, number of plots	Number of trees per ha	Mean diameter at breast height, cm	Mean height, m	Above-ground biomass, t/ha
Obuchivsky (n = 10)	740	29.1	20.7	372.3
Novokodazkuy (n = 3)	456	20.7	21.8	234.6
Pereschepunskuy (n = 3)	632	23.5	21.8	217.4
Vasilkovskiy (n = 10)	765	23.5	22.4	346.8
Verchnedneprovskiy (n = 6)	520	24.4	21.5	190.4
Novomoskovskiy (n = 8)	516	21.5	19.7	209.2

Remote sensing assessment of aboveground biomass in forest plantations. The Sentinel-2 mission provides multispectral images with a revisit interval of 5 days and is particularly well suited to determining vegetative indices (Vis), which can be used to easily translate into aboveground biomass. The SNAP software provided by the European Space Agency (ESA) for processing Sentinel-2 data includes a special biophysical processor capable of Vis.

Here, we used 4 bands of the L2A product of Sentinel-2A multispectral satellite system. Multiple regression between AGB and spectral reflectance vector ρ(B) in bands B2 – blue (460–520 nm), B3 – green (540–580 nm), B4 – red (650–680 nm), B8 – near infrared (780–900 nm) of 10 m resolution imagery was applied to the study area within woodland of Dnipropetrovsk region, Ukraine.

Multivariate regression in the form $AGB = A \times \rho(B) + c$, where {A, c} is the regression parameters vector, was restored from the Sentinel-2A multispectral image for 11/23/2019 using ground truth measurements at 40 independent spaced geopoints. Input vector – ρ(B) in our case, there was a set of Sentinel-2A spectral signals in each individual pixel of the image (P is the Earth's Surface Print, B is the band, or the operating spectral range.

In our study, we used such vegetation index as Normalized Difference Vegetation Index (NDVI) to build regression dependencies of AGB. In NDVI, the difference between the near-infrared (NIR) and red spectral bands, which is sensitive to vegetation's chlorophyll content and photosynthetic activity, is quantified (Théau et al., 2021; Vahidi et al., 2023). Therefore, NDVI strongly correlates with biomass, and it used the most frequently for estimating aboveground biomass of plantations.

Data processing and statistical analysis. We conducted the statistical analysis using the least squares method in R program. Calculation of band values obtained by remote sensing was conducted with using the open-source package SciLab. The correlation between aboveground biomass and biometric indexes at plot level and values of spectral characteristics were measured with the Pearson correlation coefficient, at a significance level of 0.05. We carried out the search for the most relevant and statistically reliable models which describe the dependences of aboveground biomass on the value of light reflection from the surface in different spectral ranges (B2, B3, B4, B8). The obtained statistical characteristics and developed models are presented with coefficients of determination (R^2) and p-value. The difference between investigated values was determined by univariate analysis of variation (ANOVA) followed by the HSD Tukey Test at a significance level of $P < 0.05$, using IBM SPSS Statistics 26 software.

Results

The values of the diameter at breast height within stands ranged from 3.9 to 30.2 cm, the height of stands ranged from 17.2 to 38.8 m, and the values of aboveground biomass ranged from 6.2 to 400 t/ha (Table 3). The mean diameter of forest stands was 19.3 cm, the mean height of stands 17.2 m, relative density 0.7 (704 trees/ha), and aboveground biomass 160 t/ha. According to statistical analysis of biometric parameters and spectral characteristics of bands, the skewness index included both positive and negative values and ranged from –2.116 to 3.163, while for kurtosis, the values ranged from –0.418 to 3.569.

We detected high ($P < 0.01$) correlations between the mean height and the mean diameter of the stand, the mean height and aboveground biomass, aboveground biomass and spectral value of the B2 band (Table 4). Moderate correlations were established between the density of plantings with mean diameter and mean height of stands, spectral value of B2, B3, B4, B8 bands with mean diameter and height of stands.

Table 3
Summary statistics for aboveground biomass (t/ha) in *P. sylvestris* and *R. pseudoacacia* plantations within Dnipropetrovsk region (x ± SD, n = 40)

Summary statistics	Diameter at breast height, cm	Mean height, m	Number of trees per ha	Aboveground biomass, t/ha	B2	B3	B4	B8
Mean value ± SD	19.3 ± 7.2	17.2 ± 6.7	735 ± 357	159.9 ± 9.0	251.2 ± 57.6	326.3 ± 99.8	305.4 ± 96.2	1901.1 ± 534.8
Coefficient of variation, %	37.8	38.8	48.6	61.9	22.9	30.6	31.5	28.1
Minimum	3.9	2.8	416	6.2	143.0	167.0	120.8	981.7
Maximum	30.2	30.5	1980	400.3	377.8	581.0	536.6	3053.1
Skewness	–2.116*	–1.378	3.163*	2.022*	1.057	2.502*	1.347	1.225
Kurtosis	–0.335	0.102	3.569*	0.258	–0.418	0.913	0.331	–0.062

Note: *statistically significantly different at $P < 0.05$; B2 – blue, B3 – green, B4 – red and B8 – near infrared bands.

Table 4
Pearson correlation coefficients between biometric indexes of forest plantation and satellite image bands (n = 40)

Biometric indexes	Diameter at breast height, cm	Mean height, m	Number of trees, stem/ha	Aboveground biomass, t/ha
Mean height, m	0.927	–	–	–
P	10^{-4}	–	–	–
Number of trees, stem/ha	–0.482	–0.352	–	–
P	10^{-3}	$2.6 \cdot 10^{-2}$	–	–
Aboveground biomass, t/ha	0.765	0.840	–0.262	–
P	10^{-3}	10^{-4}	$1.02 \cdot 10^{-2}$	–
B2	0.577	0.626	–0.096	0.836
P	10^{-4}	10^{-4}	$5.5 \cdot 10^{-2}$	10^{-4}
B3	0.620	0.686	–0.254	0.889
P	10^{-4}	10^{-4}	$1.1 \cdot 10^{-2}$	10^{-4}
B4	0.518	0.579	–0.165	0.827
P	$6 \cdot 10^{-4}$	$1 \cdot 10^{-4}$	$3.1 \cdot 10^{-2}$	10^{-4}
B8	0.617	0.662	–0.209	0.827
P	10^{-4}	10^{-4}	$1.9 \cdot 10^{-2}$	10^{-4}

Determination coefficient of multiple regression was $R^2 = 0.938$ with a root mean square error (RMSE) of 23.46 t/ha, which is a reasonably good result (Fig. 2). The aboveground biomass estimation for the forest distribution within investigated study area is presented in Figure 3. The creation of a map of the distribution of aboveground biomass was carried out in accordance with the map of forests of Dnipropetrovsk region based on the shape files available for this area. In order to show the aboveground biomass accumulation in more detail, we selected one of the studied forest districts shown on an enlarged scale.

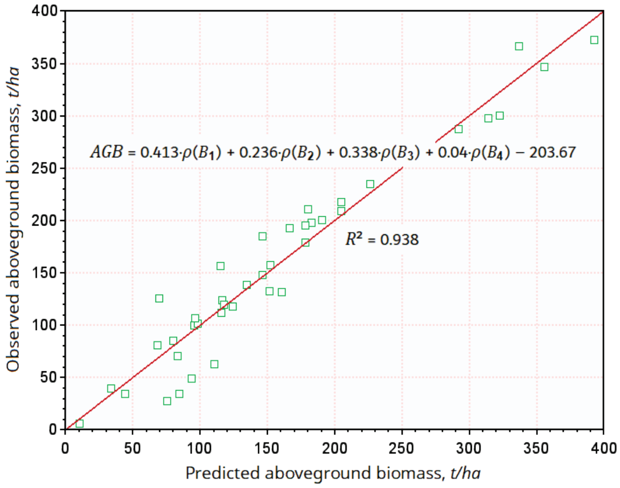

Fig. 2. Predicted/observed multiple regression dependence of aboveground biomass in Scots pine and black locust stands (n = 40)

Discussion

Climate change, extreme events, in particular changes in precipitation and increased drought frequency, have a significant impact on the prevalence and structural characteristics of forests. In addition to these unfavorable factors, forest stands (in particular, Scots pine and black locust) in Ukraine are now exposed to the catastrophic impact of current military operations caused by Russia and their already existing consequences. Taking into account that pine and black locust stands cover about 60% of forests and perform important sanitary protection functions (Sytnyk et al., 2018), mapping these areas to identify changes in aboveground biomass is important primarily for management solution.

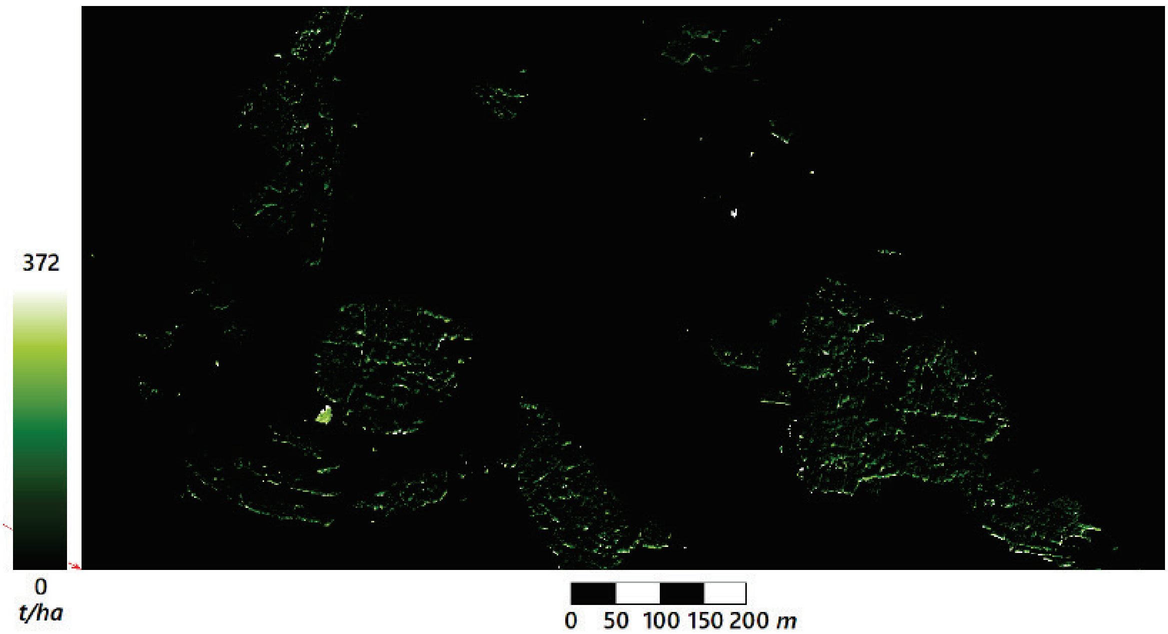

Fig. 3. Spatial distribution of aboveground biomass within Obuchivka forestry

Numerous studies have been conducted to evaluate and develop biomass functions for *P. sylvestris* and *R. pseudoacacia* in various countries around the world (Repola, 2009; Repola & Ahnlund Ulvcrona, 2014; Rusnak et al., 2022). Until now, it is considered that the destructive method is the most accurate for determining tree biomass, but it is quite clear that it takes unnecessarily long and is very expensive. In fact, the development of allometric ratios has been put into practice to reduce the cost of forest and the level of its destruction, as well as to assess carbon reserves in the stand. As single studies show, biomass assessment models developed for *P. sylvestris* and *R. pseudoacacia* provide valuable information for estimating aboveground biomass at both tree and plantation levels (Repola, 2009; Lovynska et al., 2018; Lovynska et al., 2022). First of all, the stem diameter at a height of 1.3 m is a reliable predictor for estimating the aboveground biomass of individual trees with a small margin of error (Wegiel & Polowy 2020). At the plantation level, when developing models for estimating productivity and biomass accumulation in pine and black locust plantations, the stand density and root area were important indicators as independent variables. In particular, high-density stands was found to cause an increase in the biomass of stands and a decrease in the biomass of individual trees because of competition for limited resources (West, 2014).

In this study, to build a model within selected plots in Scots pine and black locust forests, we calculated aboveground phytomass using stem diameter, tree height, wood density, i.e. parameters widely used in field experiments by researchers from all over the world (Fassnacht et al., 2021). For this purpose, we used the multivariate procedure as an effective method for regression models, despite the imbalance of data in terms of variable response, that is, in the case when not all components of biomass were measured on sample trees. Based on the proven statistical relationship between biomass equations, the multivariate procedure has some advantages over equations evaluated independently (Repola & Ahnlund, 2014).

We developed a simple approach for monitoring changes in Scots pine and black locust plantations in the temperate zone by combining land data with the results of Sentinel-2 satellite images. We analyzed the sensitivity of various Sentinel-2 indices and ranges. Compared to other sensors, Sentinel-2 has three spectral bands with a red-edge region, which are highly sensitive to the content of chlorophyll and nitrogen and do not depend on structural properties (Clevers & Gitelson, 2013; Grabska et al., 2020; Rusnak et al., 2022).

It should be noted that today there is quite a significant amount of data on the biomass of tree stands, which is obtained using remote methods (Lesiv et al., 2019; Myroniuk et al., 2020, 2022). Some of them are focused on individual zones on the regional/landscape level of Ukraine (Holiaka et al., 2021; Zadorozhniuk, 2023). However, such studies are only represented in a small number for Dnipropetrovsk region (Lovynska et al., 2021). The proposed methodology uses data and open-source software for processing of images and algorithms to estimate the biomass of forest stands with preliminary modeling of the data obtained in field experiments.

In this work, we used the principles of constructing linear and nonlinear dependencies using such spectral bands as B2, B3, B4, and B8 to model the aboveground biomass of plantings. They were most correlated with the biomass values obtained in field experiments. Those particular data of these spectra are widely used by researchers to estimate biomass (Askar et al., 2018; Khan et al., 2020). At the same time, it should be noted that the authors often add indicators of spectral bands B5, B6, B11, and B12 to the listed ones (Fassnacht et al., 2021). It is believed that the accuracy of calculating individual vegetative indicators, and therefore the indicator of aboveground biomass, may increase in this case. It should be noted that in the course of previous calculations during our studies, we detected no improvement in the accuracy of the regression model when using the listed additional spectra, so they were not used in constructing the corresponding models.

Regression equations of both linear and nonlinear forms are often used to calculate the biomass of plantings (Vahidi et al., 2023); we also used these equations in our research. The accuracy of using such models is often similar, or can be higher/lower.

The most accurate model obtained in this study described the biomass of stands using multiple regression ($R^2 = 0.94$; RMSE = 23.46 t/ha) and slightly different from data obtained by authors who used similar methodological approaches to estimate pine forest structure and map the aboveground biomass by processing Sentinel-2 images (RMSE = 40.16 t/ha) (Puletti et al., 2019; Fassnacht et al., 2021). Similar to our results, the above-mentioned researchers estimated biomass in forests relatively uniform in structure, where the stand height can often be accurate predictor (Tojal et al., 2019). When evaluating single-storeyed forests, the multiple linear regression method can also provide a more accurate estimation of the volume reserve of Scots pine, in particular, compared to the random forest (RF) method when using Sentinel-2 (Hawryło & Wężyk, 2018). The biomass of plantings can be estimated with even greater accuracy if the time shift between the acquisition of field data and structural remote sensing data is smaller (Navarro-Cerrillo et al., 2017).

Improving the accuracy of regression equations can be associated with the use of other methods of statistical analysis and modeling, and, moreover, with the addition of data obtained from additional resources, for example, satellite images from Sentinel-1, Landsat-8. In addition to methods for building the regression dependencies, the machine learning algorithm has recently been used to more accurately estimate the aboveground biomass of stands, using RF, Support Vector Regression (SVR), and Artificial Neural Networks (ANN) techniques (Vahidi et al., 2023; Vyvlecka & Pechanec, 2023; Velasco Pereira et al., 2023). Adding the SAR variable extracted from Sentinel-1 images to the SVR model improved the accuracy of the model, being a valuable set of source data related to the structure of plant objects (Nuthammachot et al., 2020). In some cases, data obtained in processing of satellite images from SAR provide more accurate estimates of forest structural variables, with approximately 15–20% of root-mean-square deviation for the AGB estimation and 5–10% of root-mean-square deviation for the mean stand height values (Martin et al., 2021; Guerra-Hernández et al., 2022).

As with the correlation analysis data obtained by us, a significant number of studies (Brown et al., 1989; Sousa et al., 2015; Gonçalves et al., 2017) were found that, combining remote sensing data from satellite images of various spatial resolutions with spectral ranges in the visible region (Blue, Green and Red) and the infrared region (Nearinfrared) and/or vegetation indices) with field data, have a strong correlation with aboveground biomass. The revealed correlations between the equations of random parameter allow information to be transferred from one equation to another, which is especially useful in calibration of the model for a new stand (Repola, 2008).

Overall, as some researchers have pointed out (Adam et al., 2020; Ziemer et al., 2023), the results of aboveground biomass modeling using biometric indicators, in particular, stand height, for different types of forests can be improved by replacing the widely used LIDAR, Sentinel-2 satellites with TanDEM-X SPC CHM (canopy height model), which better corresponds to the data obtained in the field. However, access to the high spatial resolution CHM model is still cost-limited and requires participation of aerial campaigns, that are expensive or impossible (Jin et al., 2020; Fassnacht et al., 2021), Unfortunately, this model is difficult to apply in rural areas and, in general, in many economically less developed countries, including Ukraine. But satellites such as LiDAR (Li et al., 2017), Landsat (Wang et al., 2019), Sentinel-1 (Naidoo et al., 2019), Sentinel-2 (Filho et al., 2020), etc., can be used alternatively, with a worldwide data source available for obtaining models of biomass dependencies for plant communities.

It should be considered that the described study is limited, since the developed models are specific to *P. sylvestris*, *R. pseudoacacia* and are limited to the area under study. Therefore, when applying the presented models, other factors should be taken into account, in particular, such as terrain conditions, tree age and characteristics, which can significantly affect the assessment of stand biomass. However, in general, in the perspective of applying the described integrated approach, we should agree with Vyvlecka & Pechanec (2023), who noted that currently there are still not enough data in the public domain with very high resolution to accurate estimation of the parameters in forest stands. It means the lack of data that meets the criteria for very high spatial resolution, near-infrared, thermal infrared, weekly time resolution, and free data access. Of course, addressing these issues will be an important step in further monitoring of the biomass in forest stands.

Conclusions

As our research showed, the mean diameter of forest stands ranged from 20.7 to 29.1 cm, the mean height from 19.7 to 22.4 m, and aboveground biomass from 190.4 to 372.3 t/ha. The search for correlation dependencies revealed the presence of strong reliable relationships between the taxational parameters of stands as mean height, mean diameter, and aboveground biomass, as well as between aboveground biomass and spectral value of B2 band. As regression analysis has shown, the dependencies of aboveground biomass on spectral characteristics are best described by multiple regression and the exponential model. Determination coefficient of multiple regression was $R^2 = 0.938$ with RMSE of 23.46 t/ha. Based on the results of multiple regression between AGB and spectral reflectance vector in bands B2, B3, B4 and B8, we built a map of the aboveground biomass distribution for Scots pine and black locust stands within the study region.

Comparison of obtaining data from aboveground biomass of Scots pine and black locust plantings using field and remote experiments revealed minor deviations in accordance with RMSE indicators, which indicates the possibility of applying the developed regression equations in lowland forests. Our obtained results represented a significant step towards the development of a monitoring system for assessment of aboveground biomass in coniferous and deciduous plantations growing in the conditions of Steppe zone with use of multispectral satellite images.

The authors declare that there is no conflict of interest.

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