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Primary forest characteristics estimation through remote sensing data and machine learning: Sakhalin case study

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Abstract. Currently, remote sensing techniques assist in various environmental applications and facilitate observation and spatial analysis. Machine learning algorithms allow researchers to find dependencies in satellite data and vegetation cover properties. One of the significant tasks for ecological assessment is associated with estimating forest characteristics and monitoring changes over time. In contrast to the general computer vision domain, remote sensing data and forestry measurements have their own specific requirements and necessitate tailored approaches that involve processing multispectral satellite data, creating feature spaces, and selecting training samples. In this study, we focus on extracting primary forest characteristics, including forest species groups, height, basal area, and timber stock. We utilise Sentinel-2 multispectral data to develop a machine learning-based solution for vast and remote territories. Timber stock is calculated using empirical formulas based on measurements of forest species groups, height, and basal area. These intermediate forest parameters are estimated using individually trained machine learning algorithms for each parameter. As a case study, we examine the Sakhalin region (Russia), which encompasses several forestries with varying vegetation properties. In Nevelskoye forestry, we achieved a mean absolute error (MAE) of 1.6m for height, 0.084 for basal area, and 47.8 m3/ha for timber stock. The results obtained demonstrate promise for further integrating artificial intelligence-based solutions into forestry decision-making processes and natural resources management.

1 Introduction

Forests play an important role in the ecosystem and have a significant impact on climate, biodiversity, and the economy. They are a source of oxygen, food, timber production, and help retain water in the soil and prevent erosion. Conducting forest inventory allows for obtaining information on the state of forest resources, assessing their potential, and determining necessary measures for their conservation and management [1]. This is crucial for forest management planning, fire prevention, monitoring of deforestation, and

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biodiversity protection. Additionally, forest inventory serves as the basis for developing a strategy for sustainable forest resource use and reducing negative environmental impacts [2].

The class or group of tree species in a forest is one of the primary parameters for assessing forest resources. Determining tree species can be done through sample plots or individual stands, typically focusing on dominant species that make up more than 50% of the area [3]. Another key parameter for forest assessment is the distinction between broadleaf and coniferous species. This differentiation helps address various ecological and forest management tasks [4]. Assessment can be conducted using artificial intelligence algorithms and available satellite data [5].

Forest height can be assessed through various methods and is considered an independent parameter, for example, in monitoring regrowth in power line corridors [6], as well as in conjunction with other parameters for comprehensive forest assessment. Lidar surveys are commonly used to assess forest canopy height by constructing a canopy height model from point clouds [7]. An alternative and less costly approach is the use of satellite data [8].

Absolute basal area represents the sum of the cross-sectional areas of all trees at a height of 130 cm per hectare of forest. In other words, the forest basal area represents the stand basal area. This parameter is determined using special instruments and can be assessed for sample plots. An alternative to ground inventory is the use of aerial photography data [9] or satellite observations [10, 11]. When determining this characteristic, it is important to consider not only the number of trees but also their age, species composition, and other characteristics. In practice, relative basal area is often evaluated using additional tabular data. Forest basal area is an important indicator for assessing the state of forest resources and determining necessary measures for their conservation and management [12, 13]. Insufficient forest basal area can lead to worsened ecological conditions, decreased biodiversity, increased risk of forest fires, and soil erosion. Therefore, monitoring forest basal area is a crucial element of forestry management and environmental policy.

There are several approaches to determine the timber stock, including both ground measurements and measurements using remote sensing data. Like all the aforementioned forest characteristics, the main drawback of ground measurements is the laborious and time-consuming nature of forest research [14]. Timber stock is a derived parameter and can be calculated based on other measurements. High-resolution aerial surveys from unmanned aerial vehicles (UAVs) and satellite images with medium and high spatial resolution with different spectral ranges are used to assess timber stock [15].

The aim of this study is to develop an effective approach based on machine learning methods for assessing forest characteristics in Sakhalin forests. The training dataset was formed from inventory measurements and multispectral images obtained from the Sentinel-2 satellite. To address the research goal, it was decomposed into a set of subtasks for determining key inventory characteristics (species groups, heights, and densities). A separate machine learning model was trained for each parameter. Subsequently, aggregation and conversion of parameters into the final target variable - timber stock - were carried out. A forest cover mask generated using the previously developed module based on Sentinel-2 satellite images from the same year as the other parameters was also used to obtain final maps. The developed methodology can be further utilised for carbon stock estimation, forest condition assessment, and making optimal decisions regarding natural resource management.

2 Materials and methods

The study is conducted for the territory of east Russia, namely Sakhalin. As reference data for determining species groups, basal area, height, and timber stock in the study, inventory data for Nevelskoye and Korsakovskoye forestry units obtained in 2018 were used. The spatial arrangement of all four forestry units is shown in Figure 1.

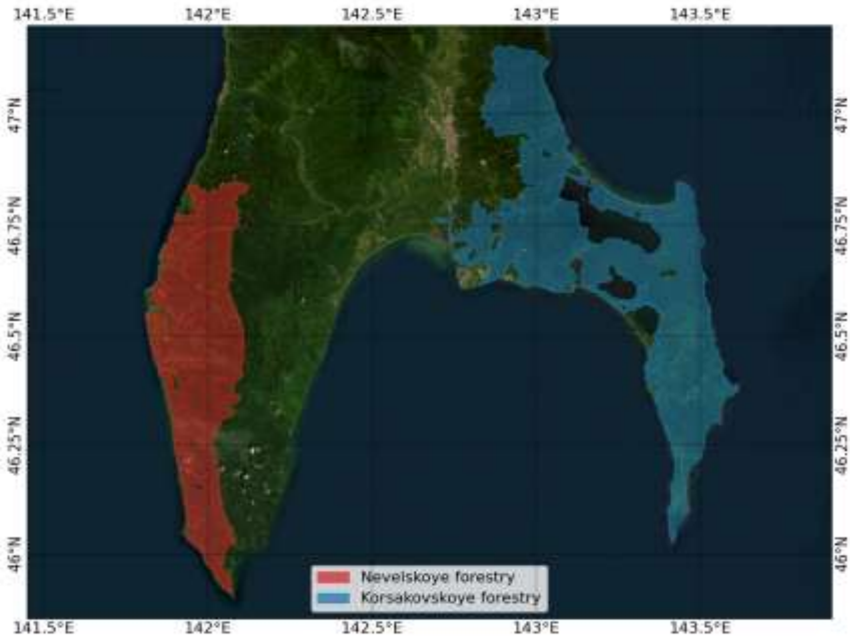

Fig. 1. Boundaries of Nevelskoye and Korsakovskoye forestry units.

2.1 Inventory data

Inventory data for Nevelskoye and Korsakovskoye forestry units are in vector format. For further analysis, the data was filtered as follows:

- Excluded all compartments with missing data for the parameters "forest_type" and "age_group"
- Retained compartments with land categories ("land_category") only from the following list: Forest plantations, Natural stands, Stands with a mix of natural and artificial species.
- For each compartment, a breakdown of the stand composition formula ("composition") was compiled, and the number of canopy layers was counted. Only single-layer individual stands were retained.
- Individual stands with a "height" parameter less than 2 metres were excluded.

After filtering, the data was further preprocessed: masks with species groups (coniferous/broadleaf) and age classes were obtained.

The species group mask was derived from the stand composition formula ("composition") as follows. Each species in the composition was assigned a group (Table 1), and the total content of broadleaf species, coniferous species, and shrubs in each compartment was calculated.

Then, the dominant group was determined for each individual stand: a group with a content of over 50%. If coniferous and broadleaf species occur in equal proportions, the stand is considered mixed, and the value "mixed" is assigned to the predominant species group of that individual stand.

Table 1 shows the data in terms of dominant species groups for each forestry unit. It is worth noting that there is no compartment where "shrub" is the predominant group. Individual stands where the dominant group cannot be clearly identified ("mixed") make up a small proportion of all stands and were therefore excluded from further consideration.

Table 1. Dominant forest groups of species.

	Nevelskoye		Korsakovskoye		Total	
	Number of stands	Total area, sq km	Number of stands	Total area, sq km	Number of stands	Total area, sq km
Coniferous	5388	442,52	23780	1202,91	29168	1645,43
Deciduous	4792	409,05	9350	491,00	14142	900,05
Mixed	881	86,71	1517	91,43	2398	178,14

As a result, data on 43,310 compartments with a total area of 2,545.47 square kilometres remained. Reference data for individual stands stored in vector format were converted to raster format according to the resolution of images obtained from SentinelHub, as described in the following section.

2.2 Satellite data

The research utilised multispectral data from the Sentinel-2 satellites. The images were downloaded from the SentinelHub service [16], which provides up-to-date data as well as archives dating back to January 2017.

The basic data preprocessing included atmospheric correction and was implemented using tools provided by the SentinelHub service. The images were processed to Level 2A. The following spectral channels with spatial resolutions of 10 and 20 metres per pixel were used for the research: B02, B03, B04, B05, B06, B07, B08, B8A, B11, B12. A description of all Sentinel-2 spectral channels is provided in Table 2. All channels were resampled to a resolution of 10 metres using nearest neighbour interpolation.

Table 2. Description of Sentinel-2 multispectral data.

Band	Description	Spectral range, mkm	Spatial resolution, m
B01	Coastal aerosol	0.433 – 0.453	60
B02	Blue	0.458 – 0.523	10
B03	Green	0.543 – 0.578	10
B04	Red	0.650 – 0.680	10
B05	Vegetation Red Edge	0.698 – 0.713	20
B06	Vegetation Red Edge	0.733 – 0.748	20
B07	Vegetation Red Edge	0.773 – 0.793	20
B08	NIR	0.785 – 0.900	10
B8A	Narrow NIR	0.855 – 0.875	20
B09	Water vapour	0.935 – 0.955	60
B10	SWIR – Cirrus	1.365 – 1.385	60
B11	SWIR-1	1.565 – 1.655	20
B12	SWIR-2	2.100 – 2.280	20

In addition to the multispectral channels, the SentinelHub service allows access to several other useful products: CLP – Cloud Probability (based on s2cloudless) [17] with a resolution of 160 metres, and dataMask – a mask with pixels labelled as "no_data" at a resolution of 10 metres. CLP values range from 0 to 255, and to obtain the probability of clouds in a pixel, this value needs to be divided by 255. dataMask has two values: 0 - if there is no data in the pixel, and 1 - otherwise. These masks will be used for cloud scene filtering in further analysis.

Downloading images for each region of interest was done using a grid with dimensions of 2560 metres x 2560 metres in the local coordinate reference system (crs) EPSG:32654. For each file containing forest boundaries in vector format, a set of non-overlapping square vector polygons with dimensions of 2560 metres x 2560 metres was obtained, with sides parallel to the forest boundaries. One element of this grid (polygon) is called a "patch". The number of patches for each forest depends on its area. Table 3 contains detailed information about each constructed grid for all forests.

Table 3. Forest area and number of patches in grids.

Forestry	Area in local crs, ha	Area in local crs, km^2	Number of patches
Korsakovskoye	$2.059 \cdot 10^5$	2059.2	457
Nevelskoye	$1.251 \cdot 10^5$	1250.9	262

Figure 2 illustrates all the obtained patches for the Korsakovskoye and Nevelskoye forests. It also includes information on the division into training and testing datasets - a necessary step for training and validating any machine learning model. The splitting into training and test subsets equals 83% and 17%, respectively. For Nevelskoye, we used 218 patches for training and 44 for testing. For Korsakovskoye, we used 380 patches for training and 77 for testing. Data in the training dataset is used for normalising input data (to be described in detail below) and optimising model parameters, while data in the testing dataset is only used to evaluate the model's performance.

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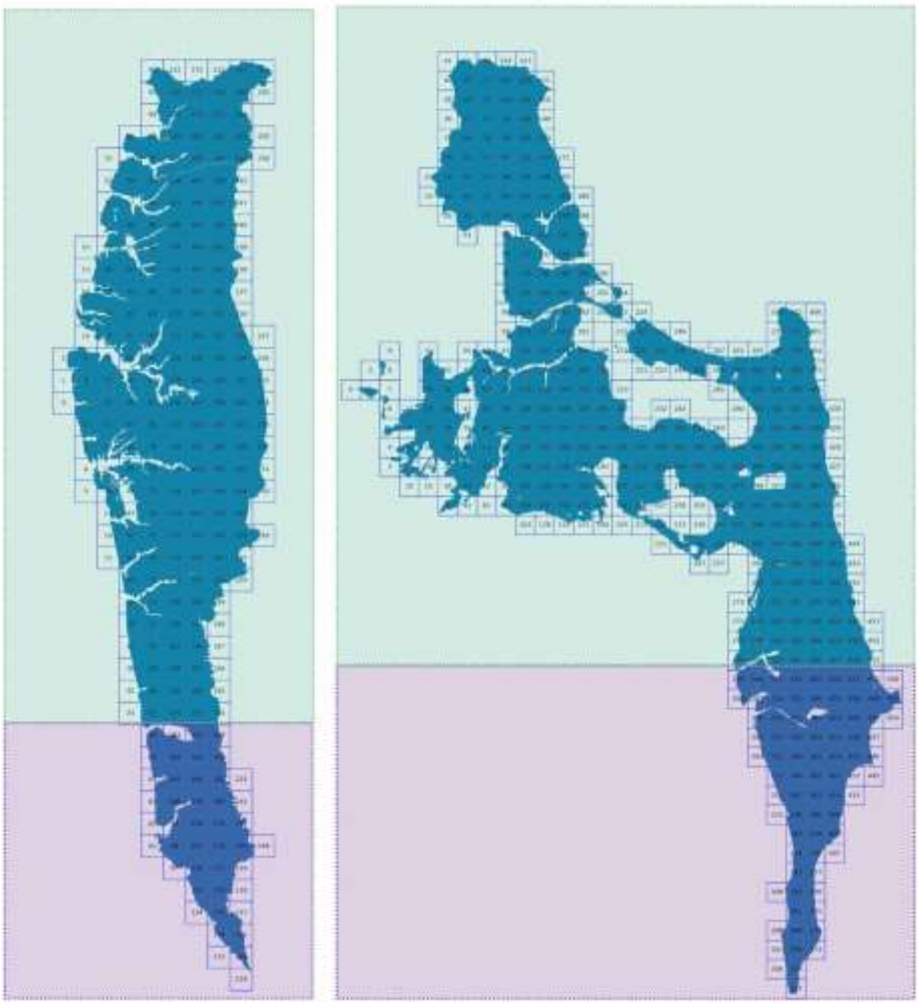


Fig. 2. Grid for Nevelskoye (the left image) and Korsakovskoye (the right image) forests, as well as division into testing and training datasets. The green area is for the training sites, the purple area is for testing sites. The patches have the size 2560*2560 m.

For each patch, all available images from January 1, 2018 to December 12, 2018 were downloaded with a cloudiness parameter of less than 30%. The year of capture was chosen based on the year of inventory observations. The cloudiness parameter is calculated for the entire tile containing the region of interest and is automatically provided with Sentinel-2 products. Examples of all downloaded RGB images for one of the patches are shown in Figure 3.

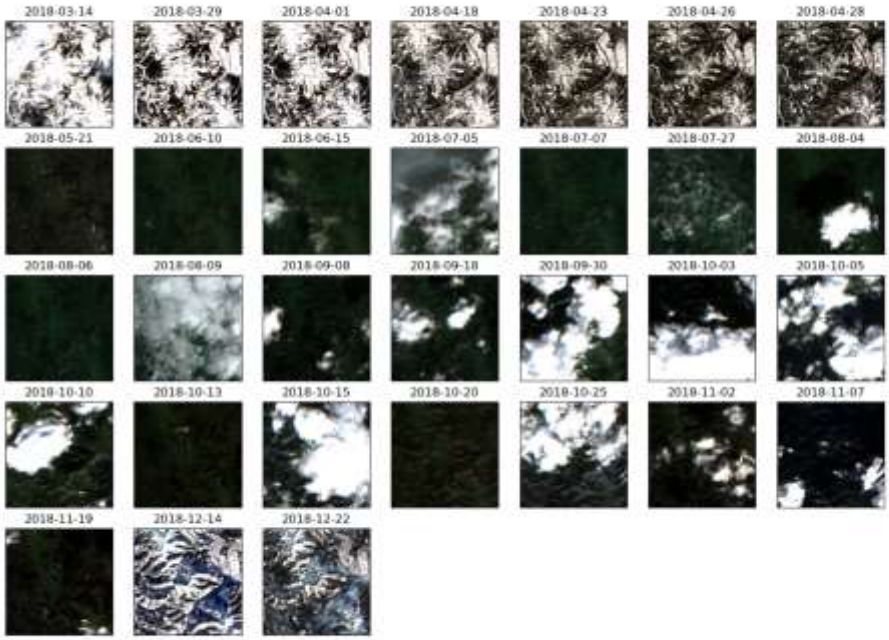
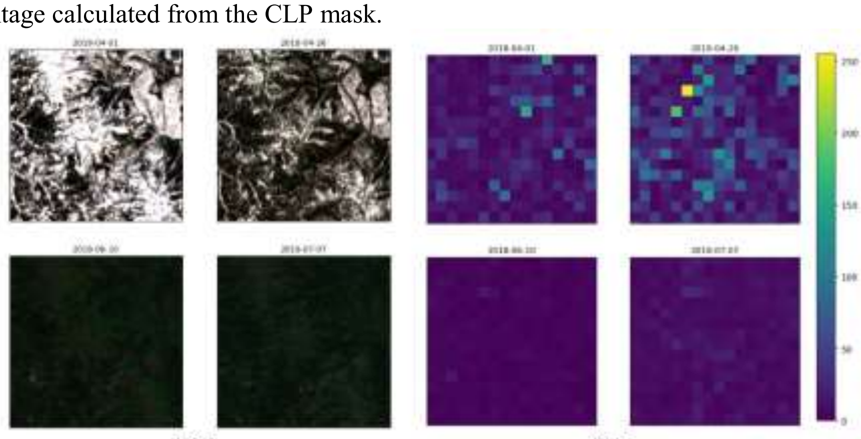
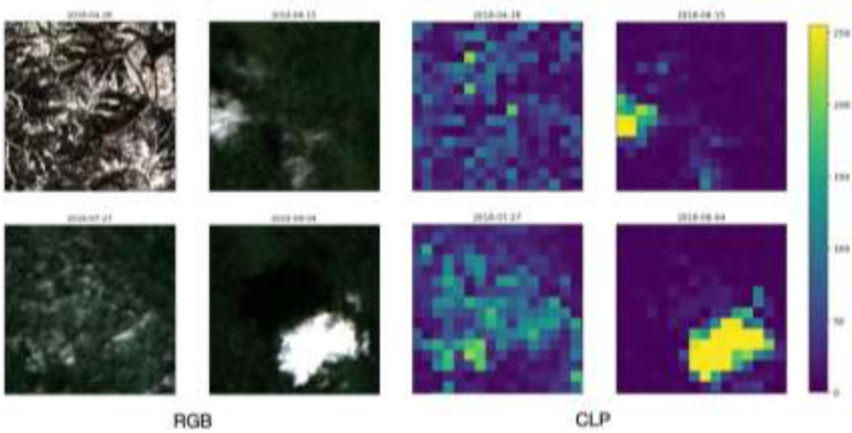


Fig. 3. Example: all downloaded RGB images for one of the patches of the Nevelskoye forest.

Since the cloudiness parameter is a characteristic of the entire tile, it is not informative for assessing cloud cover at a local level, for example, at the patch level, as shown in Figure 3. Therefore, additional filtering of cloudy images is necessary. This was done as follows. For each patch and each available date, the cloud cover percentage was calculated as the ratio of the number of pixels with a cloud probability mask (CLP) value greater than 0.5 to the number of pixels with available data (dataMask). Thus, each patch and date have a scalar parameter ranging from 0 to 1, where lower values indicate fewer cloudy pixels in the image. All images with a cloud cover percentage above 0.08 were removed from further consideration as they do not provide value for determining forest characteristics. Figure 4 illustrates an example of dividing images into cloudy and cloud-free based on the cloud cover percentage calculated from the CLP mask.



(a)



(b)

Fig. 4. Example: division of images into cloud-free and cloudy based on cloud cover percentage calculated from CLP mask. Images with cloud cover less than 0.08 (a), images with cloud cover more than 0.08 (b).

The data in the multispectral channels have integer values (uint8). It is important to normalize the input data for using deep learning methods [18]. In this study, linear normalisation is used:

$$x`_{ij} = (x_{ij} - c)\frac{b - a}{d - c} + a, \tag{1}$$

where x_{ij} is an input value, $x`_{ij}$ is a normalised pixel value, a, b, c, d are coefficients. This normalization linearly transforms values of a variable lying in the range [c, d] to the range [a, b]. The values of 0 and 1 were chosen as coefficients [a, b] in this study.

There are many ways to choose values for c and d, one of them is to take the minimum and maximum values of the input data. The problem, especially in the case of data with a long-tailed distribution, is that one outlier value can significantly affect the values of c or d, leading to very non-representative scaling. A more reliable approach is to choose c and d at the 1st and 99th percentiles of the value histogram - this reduces the influence of outliers on scaling.

Additionally, it is important to consider that images vary significantly by season. For example, during winter with the appearance of snow cover, the reflectance of the Earth's surface increases in a certain range of wavelengths, causing values in channels B02 - B8A to increase compared to values in the same area during summer. Therefore, percentiles selected for snowy images may not be suitable for non-snowy images and vice versa. To address this issue, it was proposed to normalise images separately for snowy and non-snowy periods. For each patch, images obtained during non-snowy periods (from April 20 to November 30, 2018) and snowy periods (from January 1 to April 19, 2018, and from December 1 to December 31, 2018) were separated. Then, the 1st and 99th percentiles for each of the 10 channels were calculated separately for all non-snowy images from patches belonging to the training dataset. Similarly, another set of ten 1st and 99th percentiles were obtained for snowy images. Subsequently, all images were normalised according to the required values of c and d for both training and testing patches. Table 4 contains the values of the obtained coefficients for snowy and non-snowy images. Figure 5 shows examples of RGB images from the training dataset.

Table 4. Coefficients c (1st percentile) and d (99th percentile) for normalisation for Sentinel-2 bands.

Bands	**B02**	**B03**	**B04**	**B05**	**B06**	**B07**	**B08**	**B8A**	**B11**	**B12**
	Period without snow (20.04 - 30.11)									
The 1st percentile	1	51	11	1	1	1	1	1	1	3
The 99st percentile	4520	4728	5044	5169	5372	5551	5944	5630	3077	2125
	Period with snow (01.01 - 19.04 and 01.12 - 31.12)									
The 1st percentile	1	1	1	1	1	1	1	1	1	1
The 99st percentile	9808	9520	9856	10004	9841	9548	10256	9272	1779	1675

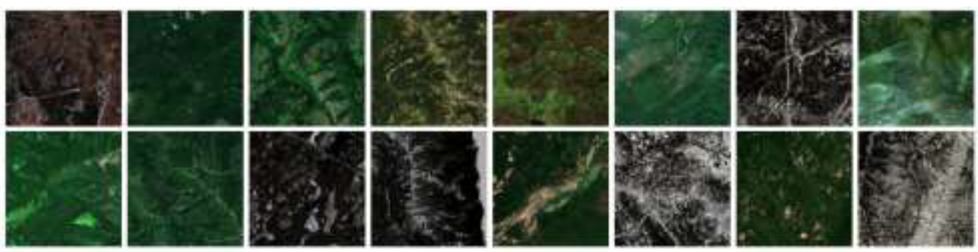


Fig. 5. RGB images from the training dataset after filtering by cloud cover percentage and normalisation.

2.3 Machine learning approaches for forestry characteristics estimation

2.3.1 Timber stock estimation

The timber stock in the stand depends linearly on the average height and basal area. The relationship varies for each species. In this study, different species were grouped into two categories (coniferous and deciduous), accordingly, the timber stock is calculated for coniferous and deciduous species.

The coefficients of the linear relationship between the timber stock and the product of height and basal area were found from the provided survey data. Figure 6 illustrates the linear relationship. Based on these plots coefficients are computed. Information about the coefficients is presented in the following formulas for coniferous (Formula 2) and deciduous (Formula 3):

$$\textit{timber stock} = 22.193 * \textit{height} * \textit{basal area} - 21.306, \tag{2}$$

$$\textit{timber stock} = 10.852 * \textit{height} * \textit{basal area} - 3.048 \tag{3}$$

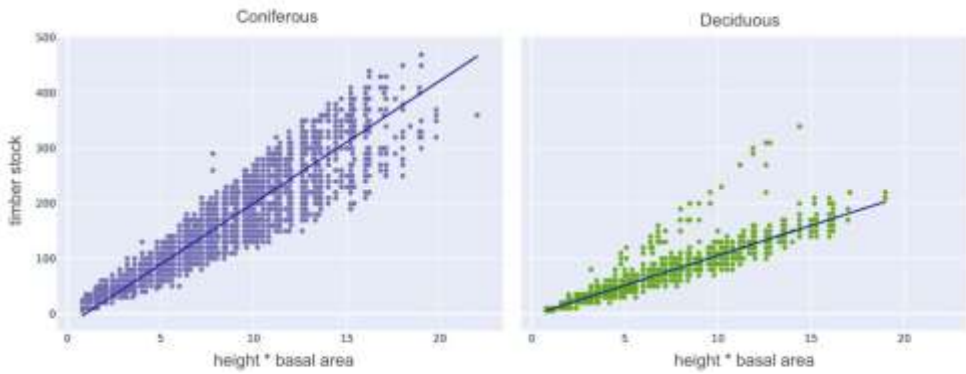


Fig. 6. Linear correlation between timber stock per hectare and the product of height and basal area from survey data.

Thus, to predict the timber stock per hectare, three parameters need to be known: the species group (coniferous/deciduous), height (in metres), and basal area (in relative units). These parameters are predicted by three separate machine learning models based on multispectral data for the year 2018. Then, the obtained characteristics were recalculated according to the formulas presented in Figure 6 to estimate the timber stock.

The final predictions are further intersected with a forest mask obtained using previously developed neural network algorithm for land cover classification [19]. The forest mask is a map where pixels take two values: 1 if there is a forest area in that pixel, and 0 if not.

2.3.2 Forest species estimation

The task of determining the species group (coniferous/deciduous) was formulated in terms of semantic segmentation. The U-Net architecture was used to solve it.

U-Net is a convolutional architecture for fast and precise semantic image segmentation [20]. It consists of two parts: an encoder and a decoder. In the encoder part, the input image gradually decreases in height and width but increases in the number of channels. This increase in the number of channels allows the network to capture high-level features. In the decoder part, the feature map is transformed back into an image of the same size as the original input image. This is done using upsampling layers, which increase the spatial resolution of the feature map and reduce the number of channels. Connections between encoder and decoder layers are used to help decoder layers identify and refine features in the image. Finally, each pixel of the output image represents a label corresponding to a specific class in the input image.

The hyperparameters defining the UNet model used in this work: num_blocks = 4, min_channels = 32, max_channel = 512. The model architecture is implemented using the PyTorch library [21]. The PyTorch Lightning framework [22] was used for training the network. Augmentations were performed using the Albumentations library [23].

Data augmentation is a popular regularisation technique involving changes to data [24]. During training, the following augmentations were applied: flipping (albumentations.Flip) with probability p=0.3, shifting and rotating (albumentations.ShiftScaleRotate) with parameters shift_limit=(-0.0625, 0.0625), scale_limit=0, rotate_limit=(-90, 90) and probability p=0.5.

For optimization, Cross Entropy Loss function was chosen for two input classes (0 - deciduous, 1 - coniferous) with parameter ignore_index = 255 (as 255 corresponds to the "no_data" label).

The Adam optimization method was used for the experiments. Several hyperparameter configurations were tested during the experiments, and the final model was selected based on the following hyperparameters. The learning rate was adjusted using the StepLR strategy with an initial value of lr = 6e-3, a step size of step_size = 50, and a gamma coefficient of 0.1. The number of epochs was set to 300.

It is common practice to split the training dataset into training (train) and validation (val) sets to evaluate the training process. In this study, the training dataset was randomly divided into train and validation parts in an 80/20 ratio. Thus, out of all 7549 images, 6040 were included in the train part, and the remaining 1509 were in the validation part.

2.3.3 Forest height and basal area estimation

To predict the basal area and height, the method of classical machine learning was chosen - pixel-wise prediction of target values based on the values of multispectral channels in the given pixel. Gradient boosting, a powerful ensemble learning method, was selected as the regression model. Gradient boosting is a technique for building an ensemble of weak models, such as decision trees, by sequentially training each model considering the errors of the previous ones. In this work, the implementation of gradient boosting in the CatBoost library was used [25]. The following hyperparameters were selected for the models: 'learning_rate': 0.35, 'loss_function': 'RMSE', 'max_depth': 8, 'iterations': 1000.

The training dataset consists of 50,486,973 pixels with 10 values for each channel. The split into validation and training sets was conducted randomly in a 15/85 ratio.

2.4 Evaluation metrics

For the regression machine learning tasks the commonly used evaluation metrics are MAE (Mean Absolute Error), RMSE (Root Mean Square Error). These metrics were computed in a pixel-wise manner. If $y^{\wedge}{}_{i}$ is a predicted value for the i-th pixel, and y_i is a ground truth value, than RMSE, MAE are computed for n pixels using the following formulas:

$$MAE(y, \hat{y}) = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y_i}| \tag{4}$$

$$RMSE(y, \hat{y}) = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y_i})^2} \tag{5}$$

From the perspective of machine learning tasks, predicting the group of coniferous/broadleaf species can be formalised as a semantic segmentation task into two classes. For such tasks, three metrics are often used: precision, recall, f1-score. The metrics are calculated on a per-pixel basis. Precision for the i-th class - the proportion of correctly predicted pixels of the i-th class among all pixels predicted by the i-th class. Recall for the i-th class - the proportion of correctly predicted pixels of the i-th class among all pixels truly belonging to the i-th class.

$$Precision = \frac{TP}{TP+FP} \tag{6}$$

$$Recall = \frac{TP}{TP+FN} \tag{7}$$

F1-score for the i-th class is an averaged harmonised between precision and recall:

$$F_1 = 2\frac{Recall * Precision}{Recall + Precision} \quad (8)$$

The classification metrics were separately computed for each class `coniferous` and `deciduous`.

3 Results

Each patch has multispectral data for several dates, hence multiple predictions for different dates. To obtain a single prediction for the year 2018, all available predictions were averaged.

Both winter and summer images were used for predicting species groups, so averaging was done for predictions throughout the year. For height and basal area, only summer images were used, so the final prediction for these parameters equals the average prediction for the period from 2018-05-30 to 2018-08-31.

The calculation of timber stock was done based on the above-described formulas for the final averaged predictions of height, basal area, and species group. Metrics were calculated on the test sites from Nevelskoye and Korsakovskoye forestries. The final results are presented in Tables 5, 6, 7, 8. The visual assessment supports the capability of machine learning models to estimate forest properties with substantial accuracy. For the forest species groups, the F1-score equals 0.694 for Nevelskoye forestry and 0.682 for Korsakovskoye forestry. Basal area and height estimation shows higher results for Nevelskoye forestry than for Korsakovskoye. The possible reason is variations in environmental conditions for this region. Finally, the timber stock calculation shows the MAE equal 47.8 m3/ha for Nevelskoye forestry and 86.7 m3/ha for Korsakovskoye.

Table 5. Metrics on the test site of Nevelskoye forestry for predicting species groups (after intersecting with the forest mask).

Species group	F1-score	Precision	Recall
Deciduous	0.705	0.683	0.730
Coniferous	0.683	0.708	0.659
Average	0.694	0.695	0.694

Table 6. Metrics on the test site of Nevelskoye forestry for predicting height, basal area, and timber stock (after intersecting with the forest mask).

Characteristics	MAE	RMSE
Height	1.6 m	2.2 m
Basal area	0.084	0.105
Timber stock	47.8 m3/ha	63.8 m3/ha

Table 7. Metrics on the test site of Korsakovskoye forestry for predicting species groups (after intersecting with the forest mask).

Species group	F1-score	Precision	Recall
Deciduous	0.715	0.697	0.733
Coniferous	0.649	0.669	0.630
Average	0.682	0.683	0.681

Table 8. Metrics on the test site of Korsakovskoye forestry for predicting height, basal area, and timber stock (after intersecting with the forest mask).

Characteristics	**MAE**	**RMSE**
Height	2.8 m	3.9 m
Basal area	0.14	0.16
Timber stock	86.7 m3/ha	110.3 m3/ha

Figures 7-10 show maps with predictions and reference data for the example of the test site of Nevelskoye forestry.

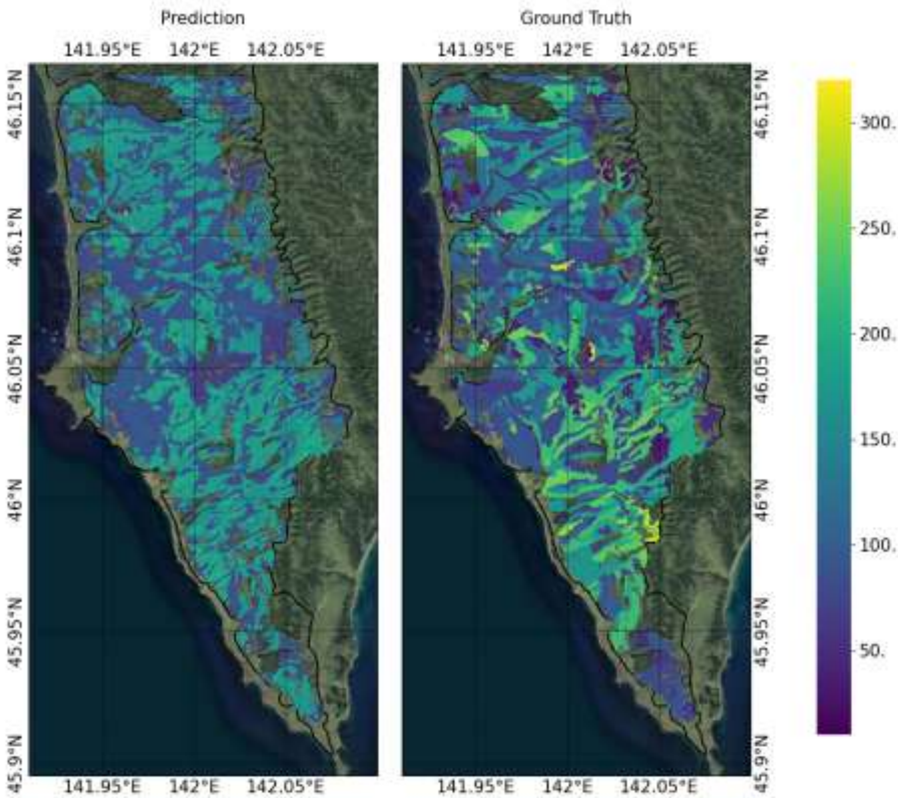


Fig. 7. Timber stock on the test site of Nevelskoye forestry. Timber stock is in m3/ha.

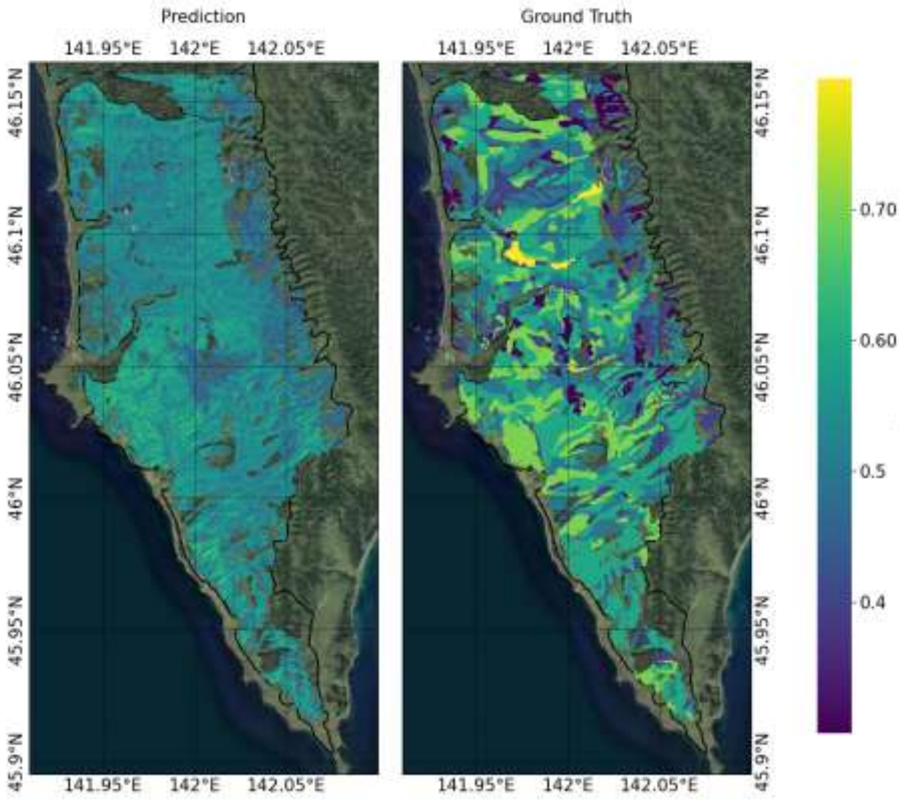


Fig. 8. Basal area on the test site of Nevelskoye forestry.

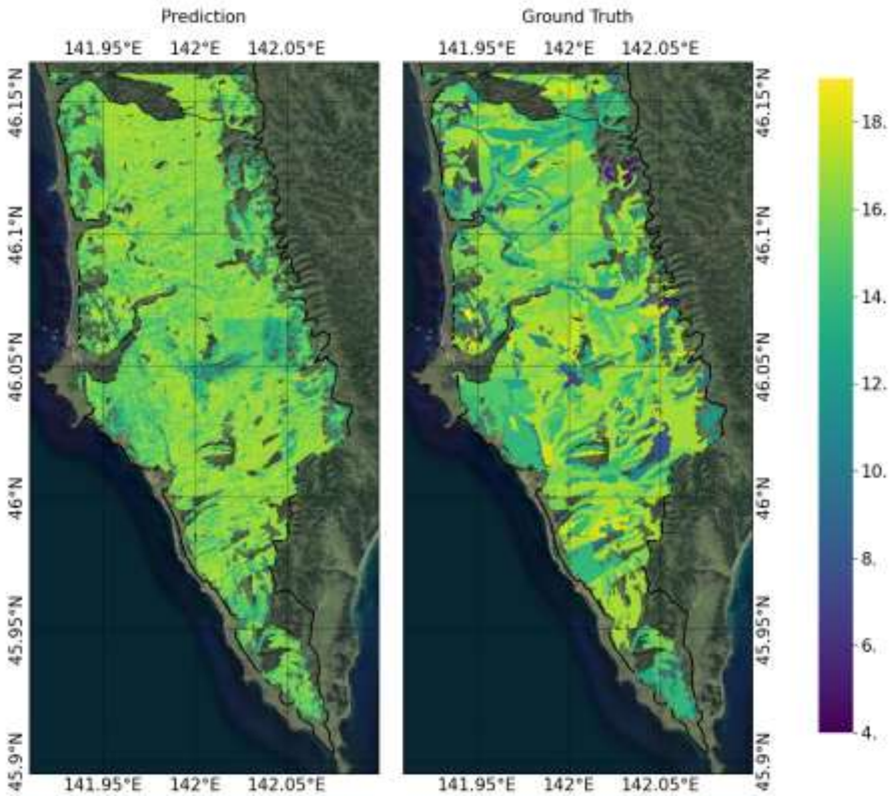


Fig. 9. Height on the test site of Nevelskoye forestry. Height is in metres.

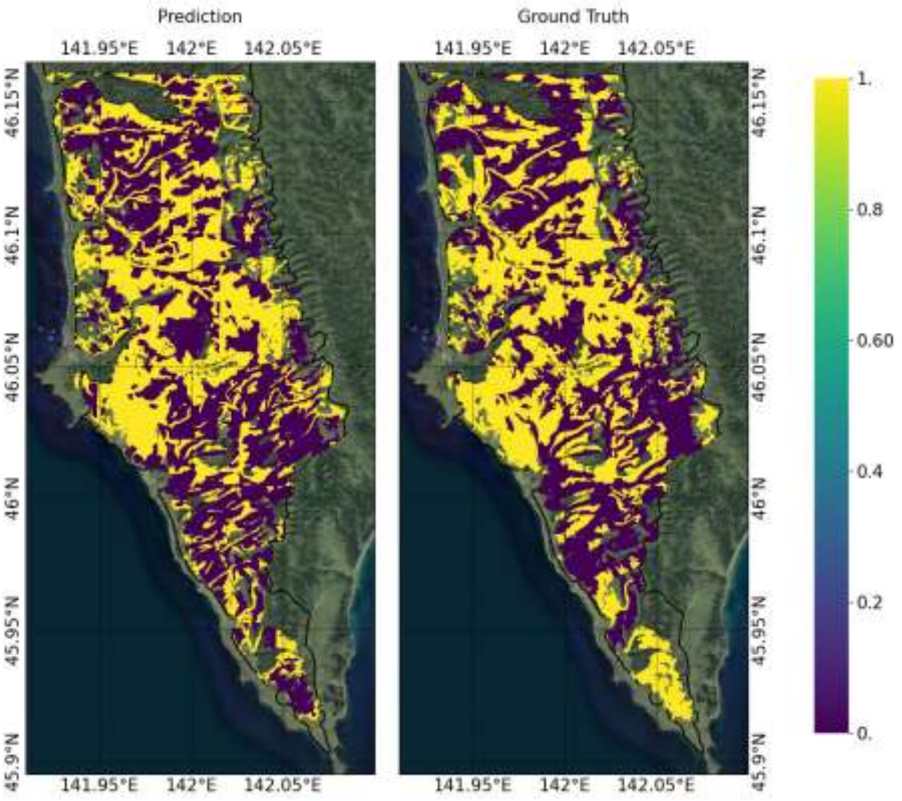


Fig. 10. Species groups on the test site of Nevelskoye forestry. 1 is for coniferous, 0 is for deciduous.

4 Discussion

Deep learning model training for conifers and broadleaf classification is presented in Figure 11. It is shown that the highest results are achieved after 200 epochs. We used full-year satellite observations to develop the forest group model. Another possible approach is to train separate models for the vegetation period and non-vegetation period to extract different spectral patterns independently. In the future studies, other deep neural networks architectures can be also examined to improve the obtained results. For instance, visual transformers have shown prominent results in various tasks in the general computer vision domain. Moreover, additional forest classes might be useful for further study and it will allow to reduce the total error of the timber stock estimation based on intermediate forestry parameters.

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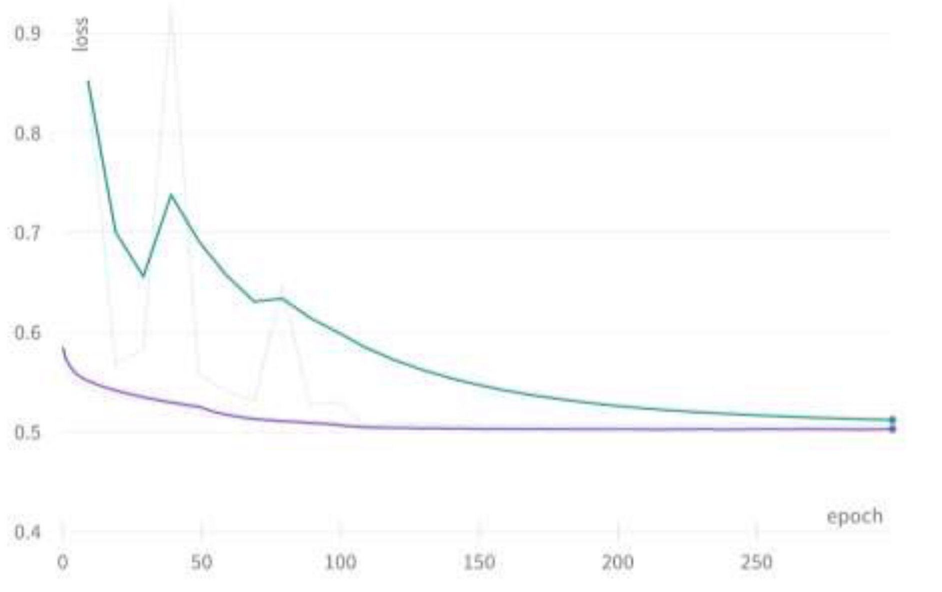

Fig. 11. Training process of the network: the green colour represents the loss function value on the train set, while the purple colour represents it on the validation set.

In this study, only spectral bands have been used to create feature space. In future experiments, the feature space can be extended by vegetation indices and LiDAR measurements for regions where such data is available. Another important forest characteristic that might be integrated into the timber stock estimation pipeline is forest age. Forest age can be accurately predicted using machine learning techniques and multispectral data processing.

Overall, advanced tools development for ecological monitoring is currently highly valuable. Satellite data usage allows researchers to conduct studies for vast territories. The proposed solution integrated freely available satellite data that can provide important spectral information. Based on the spectral values for the vegetation cover, machine learning algorithms are trained to extract significant patterns and predict the target forest properties.

The estimated forest characteristics can be utilised to calculate carbon stock in the regions of interest. It will reduce the processing time and support rapid analysis.

5 Conclusion

This study provides descriptions of experimental work on determining the relationships between forest inventory characteristics (timber stock, age, height, basal area) and remote sensing data using machine learning algorithms - gradient boosting (CatBoost) and convolutional neural networks (UNet). The study used Sentinel-2 mission images with L2 processing level for 2018, taking the following spectral channels with spatial resolution of 10 and 20m per pixel: B02, B03, B04, B05, B06, B07, B08, B8A, B09, B11, B12, all channels were resampled to 10m resolution through interpolation. Based on remote sensing data and forest inventory data, three models were trained to determine height, basel area, wood species group (coniferous/broadleaf), from which wood volume can ultimately be obtained. For Nevelskoye forestry, the achieved MAE for the timber stock equals 47 m3/ha. The results can be further integrated to monitoring systems and assist in local and global environmental studies.

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