Article

Computer Vision Approaches for Timber Volume Estimation: Northwestern Russian Boreal Forests Case Study

Svetlana Illarionova [1,*], Sergey Nesteruk [1], Vladimir Ignatiev [1], Ivan Oseledets [1], Alexey Trekin [1], Mariia Pukalchik [1], Alexander Kedrov [1], and Anton Ivanov [1]

[1] Skolkovo Institute of Science and Technology, Moscow
* Correspondence: s.illarionova@skoltech.ru

Version July 9, 2021 submitted to Journal Not Specified

Abstract: Automatic forest timber volume (FTV) estimation is crucial for carbon and water cycle prediction, assessing climate change, forest resources management, and ecosystem analysis. In recent years, various researches focused on this problem utilizing high-resolution light detection and ranging (LiDAR) data. However, this type of data requires unmanned autonomous vehicles (UAVs) to be collected. In practical application, it leads to high data collection costs. This paper considers computer vision approaches that estimate FTV using only freely available satellite images (Sentinel-2 with 10 meters per pixel spatial resolution). Therefore, the satellite-based approach needs neither additional hardware nor human resources for data collection. It makes the method scalable and allows application in hard-to-reach regions. We implemented and compared the classical machine learning approaches and deep convolutional neural networks (CNNs) for the FTV estimation task. For model training and evaluation, field-based measurements from the Russian boreal forest were used with a total area of about 200.000 hectares. The result shows the high potential of computer vision methods for robust forest resources assessment.

Keywords: Machine learning; remote sensing; forest timber volume; regression task; boreal forests.

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1. Introduction

Forest management regulations of different countries have different requirements to the forest inventory data, because of diversity of tree species, climate conditions, soil fertility and so on [1,2]. That leads to differences in approaches and in the detalization of the resulted information about forest structure.

Scalable and accurate methods of estimation main forestry parameters such as dominant forest species [3], timber volume [4] and basal area is an important problem for the management of vast territories covered by hard-to-reach forests.

A common methods for forest inventory are based on field measurements, LiDAR data and high resolution satellite imagery [5–9]. The most accurate of them also use field data accomplished by local volume tables to model tree heights and volume for each species separately [7].

This study examines different machine learning approaches to estimate mean timber volume using satellite data and supplementary materials. We consider alternative approaches that do not require extra field measurements. For machine learning models training, ground-based data is used. We conduct experiments for Russian boreal forests with a total area of 200.000 hectares.

2. Materials and methods

2.1. Study site

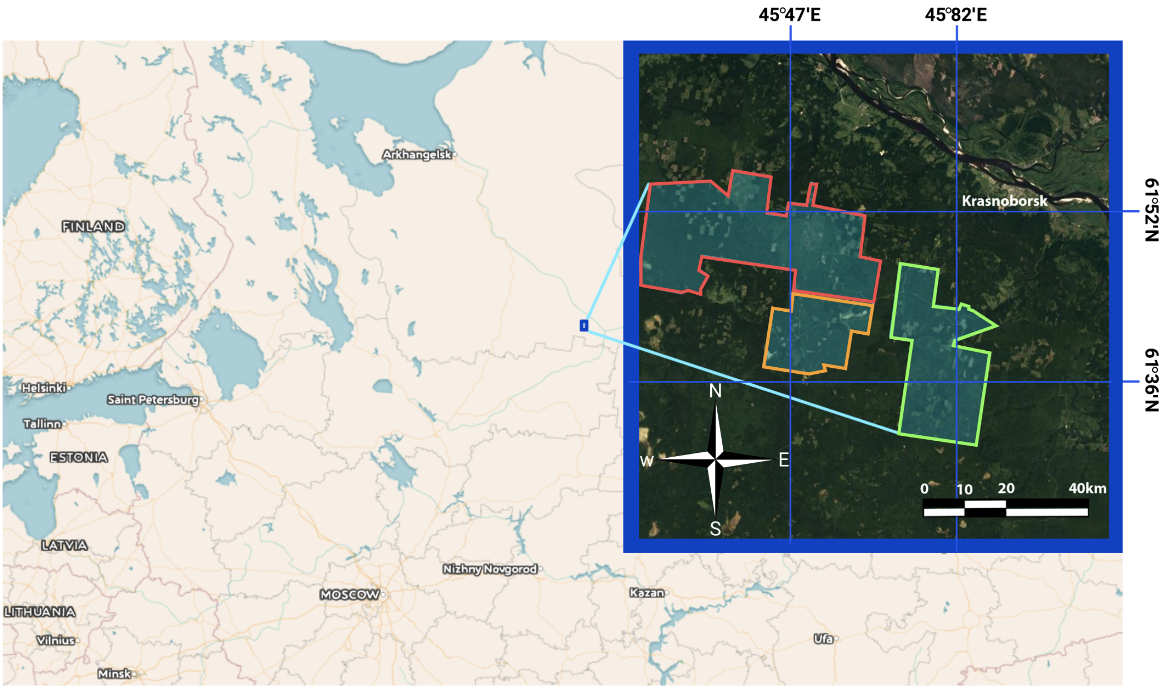


Figure 1. Region of interest. Green polygon is the training area, orange polygon is validation area, red polygon is test area.

The study is conducted for the Arkhangelsk region of northern European Russia, middle boreal zone (Figure 1). The coordinates are between $45°16'$ and $45°89'$ longitude and between $61°31'$ and $61°57'$ latitude. The total study area is about 200.000 hectares. The region has a humid climate and high cloud coverage during a year. The region's topography is flat, with a height difference between 170 and 215 m above sea level [10]. The region is covered by conifer and deciduous species: spruce, aspen, and birch.

2.2. Reference data

Machine learning algorithms and especially deep learning neural networks require a large amount of reference data to show good generalization and become stable for integrating into applied solutions. For this purpose we leverage the ideas of surrogate modelling [11] and combining real world measurements with synthetically generated data [12,13], when obtaining precise reference data is very resource-intensive and time consuming. Etalon data with the timber volume is provided in a form of a raster grid with the $16 * 16$ meters cells. Each cell stores five forestry characteristics modelled by using field sample plots, ALS data and SPOT 5 satellite images: total mean volume (V, m^3/ha), basal area (G, m^2/ha), mean tree diameter (D, cm), mean tree height (H, m) and mean age (A, years). Detailed description of the technology used to model V, G, D, H, A is presented in the work [7]. In our study we use only total mean volume (Figure 2) as an target forestry parameter to be predicted only by the remote sensing data described in the Section 2.3.

2.3. Satellite data and supplementary material

Sentinel-2 image data for this study was acquired in L1C format from EarthExplorer USGS [14]. Image IDs and acquisition dates are presented in Table 1. The Sen2Cor package [15] was used

Table 1. Sentinel images. Date format is: month, day, year.

	Image ID	Date
0	L2A_T38VNP_A005695_20160725T082012	07.25.16
1	L2A_T38VNP_A007297_20180730T081559	07.30.18
2	L2A_T38VNP_A015748_20180628T082602	06.28.18

for atmospheric correction. Irrelevant pixels were excluded for further study using cloud and shadow maps. Pixel values in L2A format were mapped to the interval $[0, 1]$ through division by 10000 and clipping to 0 and 1. We used spectral bands with a spatial resolution of 10 m per pixel ($B02$, $B03$, $B04$, $B08$ bands). Bands with 20 m per pixel spatial resolution ($B05$, $B06$, $B07$, $B11$, $B12$, $B8A$ bands) were adjusted to 10 m by nearest-neighbor interpolation.

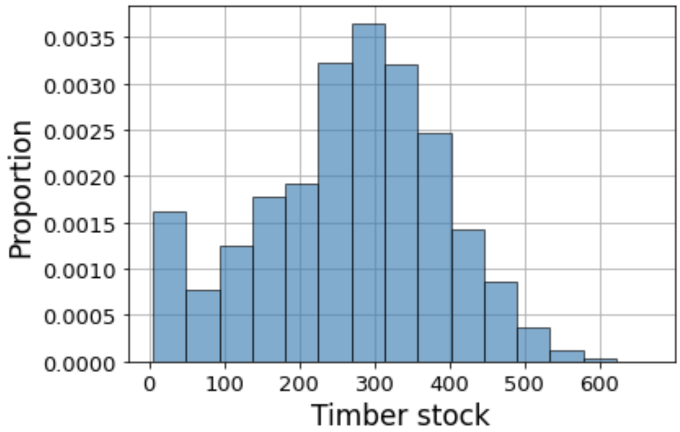


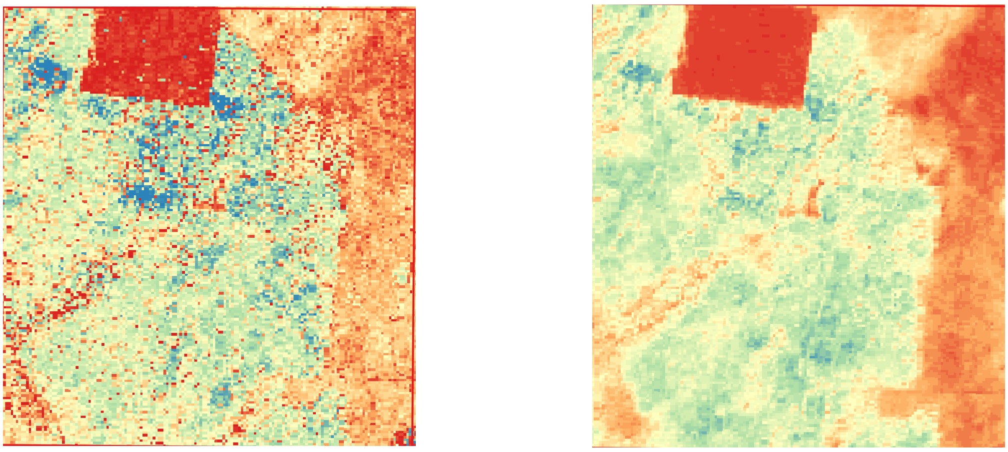
Figure 2. Volume distribution.

As it is mentioned in the Section 3 to increase the accuracy of forestry parameters estimation, in particularly timber volume modelling, information about heights of trees should be involved. The information about the heights of vegetation, in particular for the forest inventorization problem, could be accurately measured by LiDAR data captured from UAVs. The Canopy Height Model (CHM) is the most common raster representation of vegetation heights based on LiDAR. We use CHM artificially generated from the pansharped WorldView-3 satellite image with $0.6m$ resolution. The algorithms for CHM generation are provided by the geoanalytical platform Mapflow (https://mapflow.ai/). Generated CHM is downsampled to match the spatial resolution of Sentinel-2 satellite imagery. Having the spatial resolution of input images at 10 meters it is not necessary to use expensive LiDAR data, if the accuracy of the artificial height map doesn't differ a lot from the one obtained from LiDAR. Calculations show that the mean absolute error between the artificially generated CHM and extracted from LiDAR data is about 2 meters at 10 meters spatial resolution. Visual comparison of the height maps generated from WorldView-3 image and extracted from LiDAR data is presented on Figure 3.

2.4. Timber stock prediction

For timber stock estimation we used two machine learning algorithms: random forest regression (RF) [16] and gradient boosting regression (GB) [17]. Random forest operates by training many independent weak tree-based algorithms and averaging their results. Gradient boosting constructs new trees that consider the average of the previous trees.

Machine learning methods are trained on pixel data that includes different channels (Table 3). Baseline refers to ten spectral bands. *LiDAR_mode* is spectral bands data with light detection and ranging (LiDAR) data. *DEM_mode* is spectral bands data with DEM data. *LiDAR_plus_DEM* is spectral bands data with LiDAR and DEM data. *Artificial_height* is spectral bands data with approximation



(a) LiDAR- based **(b)** artificially generated from WV-3 satellite image

Figure 3. Example of CHM rasters with 10m spatial resolution obtained from different sources.

Table 2. Experiments with different input data.

Experiment	Multispectral	LiDAR	DEM	Generated height
Baseline	✓	✗	✗	✗
LiDAR_mode	✓	✓	✗	✗
DEM_mode	✓	✗	✓	✗
LiDAR_plus_DEM	✓	✓	✓	✗
Artificial_height	✓	✗	✗	✓
Artificial_height_DEM	✓	✗	✓	✓

of LiDAR data. *Artificial_height_DEM* is spectral bands data with approximation of LiDAR data and DEM data.

For the forest timber volume estimation, we also implement a CNN model. Deep neural networks have been widely used for image processing and analysis tasks when spatial characteristics are essential. As the input, it use combination of spectral bands. The model is trained to predict the timber volume values by minimizing a loss function. We use U-Net [18] architecture that has shown significant results in various computer vision tasks. ResNet-34 [19] is used as the backbone. The optimizer is Adam [20]. As the loss function, we use RMSE.

To enlarge the dataset size during CNN training, we use geometrical augmentation: random rotation and flipping.

To assess the prediction quality, we considered Mean Absolute Error (MAE) and Root Mean Square Error (RMSE, Equation 1). It is a commonly used metrics for regression tasks.

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n}, RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - x_i)^2}{n}} \tag{1}$$

where y_i is the predicted value, x_i is the true value, n is the number of observations (pixels).

3. Results and discussion

Results obtained by different models are presented in Table 3. Baseline models using just spectral data show lower results than models leveraging supplementary materials.

Examples of models predictions are shown in Figure 4. The best results were achieved by the gradient boosting algorithm. CNN model does not outperform this result. As one can see, LiDAR data is very helpful at volume estimation. As our results show, artificially generated height data can

Table 3. Experiments with different input data.

	RF mae	RF rmse	GB mae	GB rmse	U-Net mae	U-Net rmse
Baseline	62.6	84.5	62.3	83.7	63.2	85.6
LiDAR_mode	55.8	77.7	55.3	77.2	56.7	78.2
DEM_mode	66.1	87.9	65.7	87.6	65.8	87.2
LiDAR_plus_DEM	54.6	76.2	**53.9**	**75.8**	55.4	78.2
Artificial_height	56.3	78.2	56.1	78	55.9	77.8
Artificial_height_DEM	55.7	77.6	55.1	77	55.8	78.2

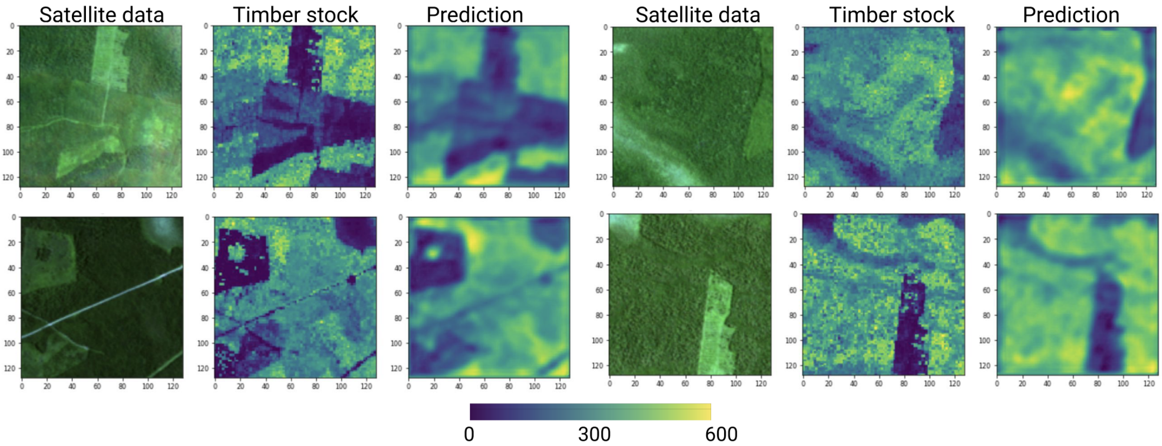


Figure 4. CNN model predictions (with artificial generated height).

efficiently substitute LiDAR data. That allows obtaining high-quality predictions utilizing only satellite data which is beneficial because airborne data is difficult and costly to obtain.

For further CNN performance improvement, we are going to use object-based [21] and multispectral image augmentation approaches [22]. These techniques show promising results on other remote sensing tasks.

4. Conclusions

Timber stock is a vital parameter for forest management and environmental studies. Remote sensing aims to provide high-quality data for large areas that can be leveraged for automatic timber stock evaluation. This study focuses on different machine learning approaches to process satellite data and predict timber stock. We also examine supplementary materials such as freely available for boreal regions digital elevation model and artificially generated landcover height map. This data allows us to improve model performance comparing with only multispectral data. Experiments show promising results for satellite-based timber stock evaluation.

Acknowledgment

The authors acknowledge the use of the Skoltech CDISE supercomputer Zhores for obtaining the results presented in this paper.

Conflicts of Interest: The authors declare no conflict of interest.

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