Methods for Updating Forestry Data Based on Temporal Analysis Using Sentinel-2 Images

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Abstract: *Currently, in many large forest areas, an inventory of tree species has not been conducted for a long time. Since sending specialists to vast territories to manually detect updates is expensive and inefficient, it has become necessary to develop an approach to automate this process. This article proposes an algorithm for refining forest inventory data using the Krasnoarmeyskoye Forestry in the Samara region of Russia as an example. Satellite images with a spatial resolution of 10 meters, obtained over several years from the Sentinel-2 satellite, served as the reference data. Subsequently, images captured on cloudless days within a calendar year were combined into a composite. The resulting composite, representing a multi-channel image, was used as a feature vector. These data were used to label forest areas and assess the performance of the classifier. However, this digital forest management data may be partially outdated and may not reflect the current state of the area. A mismatch between the classifier's results and the assigned labels may indicate either a change in tree species in the area or an error in the classifier. This study explores the potential of using a three-dimensional convolutional neural network (3D-CNN) and the support vector machine (SVM) method for updating data on tree species. Initially, these methods were used to create a final classification mask for the forest inventory being studied. Based on the classification results (achieving high accuracy was not the primary goal of the work), specific features of each classifier that are useful for updating forest inventory were identified. Based on these findings, a decision was made to develop a strategy that utilizes both approaches. Using this strategy, a technology for selecting priority points for ground verification was proposed. The effectiveness of the proposed technology was tested in practical field conditions, and the technology demonstrated an advantage over the previously used point selection method.*

Keywords: *convolutional neural networks, forest inventory data, remote sensing, Sentinel-2, temporal analysis*

Introduction

At present, the issue of regularly updating forest species data is widespread [4,8,19]. Continuously updated data are important for monitoring the behavior of different tree species under specific climatic conditions. Sending specialists into the field is a labor-intensive and costly task due to the vast areas of forest being studied. Moreover, accurate species identification in specific areas may require specialized expertise. The task of classifying forest areas has improved significantly [1, 9, 10, 12, 18, 20] and become more cost-effective since the launch of satellites, particularly Sentinel 2A, 2B, and 2C (since 2024). Satellite images are freely available and regularly updated (at least every five days). Each image is multispectral, containing 13 channels with resolutions ranging from

10 to 60 meters. Previous studies have explored the classification of forest species using satellite images [13, 16]. However, those studies used higher-resolution images of less than 2 meters and did not address the issue of updating the current forest inventory.

This study explores the possibility of classifying forest species using images with lower spatial resolution, as well as monitoring ongoing changes. However, even with a large number of satellite images, it is challenging to accurately identify all species within a specific forest plot. This difficulty may be attributed to the varying ages, heights, and crown densities of different tree species, as well as differences in trees of the same species. Additionally, multiple tree species may coexist within a single plot, further complicating the identification and clustering process. Therefore, this study sets a more practical goal: to detect forest areas that have likely changed compared to the most recent inventory data.

When studying an area, there is no certainty that the annotated data aligns with the current forest inventory due to possible updates in forest species composition. Therefore, the main objective of the developed classification model is to update information on the current species. Changes in forest species can occur when one species replaces another, due to forest fires, or cuts, or other natural events. This study primarily focuses on situations where the classifier's predictions differ from the available archival inventory data for a given plot. In cases of such discrepancies, it is logical to do some fieldwork to determine the current tree species.

If the existing data matches the classifier's results, it may suggest either that the forest in the given area has remained unchanged or the classification model mistakes. This ambiguity is important to consider when analyzing the results. The goal of the study is to develop a technology involving machine learning methods that helps reduce the time and financial costs of updating inventory data.

This approach was previously investigated in our study [2], where the classification model was based on a support vector machine (SVM). Field testing demonstrated that the proposed method can effectively detect changes in forest composition; however, it often makes mistakes and requires improvement. Additionally, the mentioned study provided practical recommendations for using the classification model to select forest areas that should be prioritized for inspection.

In the present study, we continued the work initiated in [2]. First, we applied a different classification model based on three-dimensional convolutional neural networks and compared its performance with the SVM approach. Second, we explored various methods for utilizing classification models, including the joint use of both models, to select areas. This approach allowed us to enhance the accuracy of detecting changes in the terrain.

Features of the Area

The proposed model was developed to address the problem of forest species classification using multi-temporal Earth remote sensing data. The Krasnosamarskoye forestry area, located in the Kinel district of the Samara region, was selected as the study site (see Fig. 1). The remote sensing data for tree species classification were composites created from cloud-free Sentinel-2 images of the specified area for each year from 2020 to 2023. Multispectral images were combined into composites corresponding to their respective years to provide more information for analysis. As a result, four composites were created, consisting of 200, 310, 430, and 450 spectral channels, respectively (see Table 1). The number of channels in each composite depended on the number of favorable (cloud-free, snow-free) days available for imaging in a given year. During the combination process, no dimensionality reduction was applied to avoid losing potentially important information for the classifier.

Table 1: Dimensions of the Composites.

Year	Number of Channels
2023	310
2022	200
2021	430
2020	450

Forest inventory in this territory was conducted in 2013-2014. The area was divided into 3800 forest plots. Each plot is characterized by relative homogeneity in terms of soil conditions and vegetation. Our database contains the following semantic data for each plot: species composition, indicating the percentages of each forest species (in multiples of 10%), crown density, and average tree height. In total, nine species grow in the forestry: birch, elm, oak, willow, maple, aspen, pine, poplar, and ash.

The ground truth mask was created at a 10-meter resolution, matching that of the Sentinel-2 satellite images. The dominant species in the plot corresponding to a given pixel was chosen as the class label for each pixel. In addition to the nine forest species classes, the following classes were also included: "water surface", "burnt areas and open spaces," and "buildings and roads."

A portion of the forestry pixels (a total of 833,475 points) was selected for training the classification models and analyzing their performance. The dominant species in the selected plot points accounted for at least 80%. The resulting ground truth includes 33% pines, 22% categorized as “burnt and cleared areas” ,17% oak, and 13.7% birch. The remaining six classes are represented in smaller quantities, with species such as elm, ash, poplar, and willow each comprising less than 1.5% of the total sample. Table 2 presents the complete counts of instances for each class in the ground truth mask.

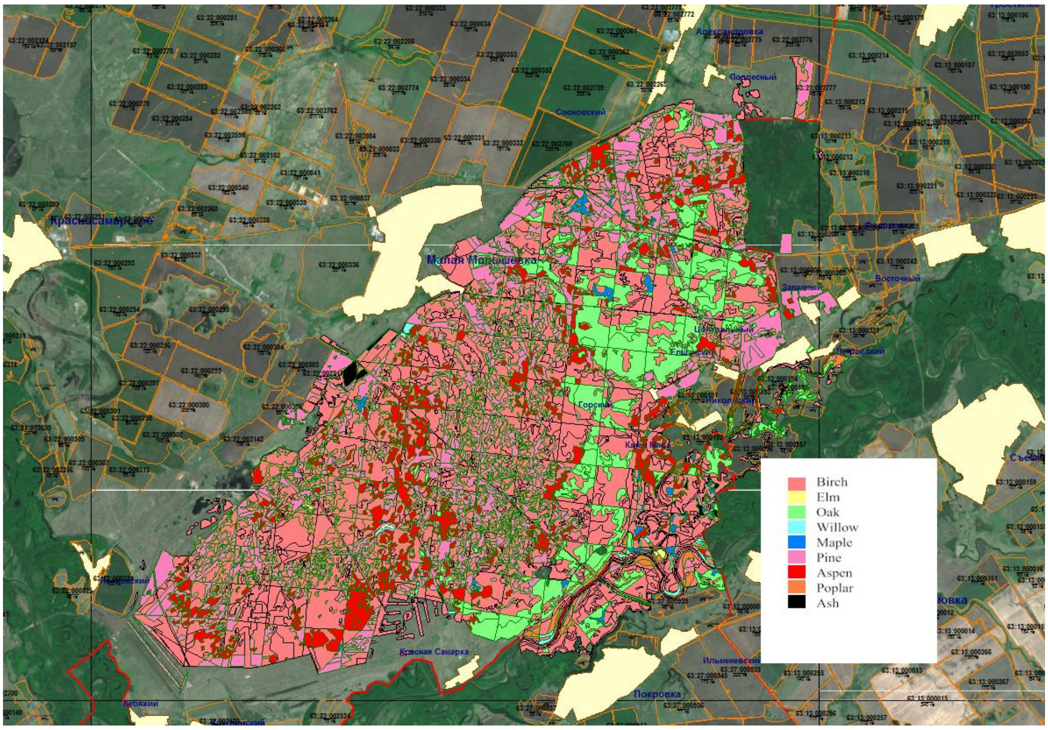

Figure 1: Tax data of Krasnosamarsky Forestry.

A Baseline Model Based on 3D-CNN for Hyperspectral Image Classification

The combination of multiple channels from multispectral images makes the resulting composite comparable in the number dimensions and the length of spectral dimension to hyperspectral images. Previous research has already been conducted to determine the best algorithm for forest species classification [3, 5, 11, 14, 15, 17] using hyperspectral images. For instance, article [11] presents studies on the classification of hyperspectral forest species data based on images from UAVs. In that study, hyperspectral data obtained through aerial imaging were used as the feature vector. Several classification algorithms were considered for this task, but the method utilizing a three-dimensional convolutional neural network (3D-CNN) yielded the best results. The following criteria were used to evaluate the classifier's performance: Accuracy, Recall, Precision, and F1-score. These metrics quantify how closely of the classifier's predictions match actual field inventory. The training was conducted on images with 250 spectral channels, covering wavelength ranges of 401.32–717.49, 723.72–892.05, 1006.17–1077.20, 1197.67–1329.06, and 1471.22–1776.93 nm.

The essence of the method proposed in [18] lies in the simultaneous extraction of spectral and spatial features using three-dimensional convolution (3D-CNN). Unlike 1D-CNN, which produces one-dimensional feature vectors, or 2D-CNN, which generates two-dimensional feature matrices, the convolutional layers in 3D-CNN create feature cubes. This allows us to extract more complex features than those manually created.

The structure of the network used in [11] consists of four convolutional layers with three-dimensional kernels, followed by two linear layers. The convolutional layers are used to extract spectral-spatial features from the input data, and the linear layers perform the final classification of these features.

The main advantage of this approach is its ability to use spatial characteristics for classification. Consequently, specific clusters with the same tree species will be identified when creating the species prediction raster. However, if multiple species are present within the same area, this may lead to classification errors.

The training process of the classifier was carried out using the AdamW optimizer with parameters β_1=0.9, β_2=0.999 and $\epsilon = 1e - 8$, with a weight decay of $wd = 0.01$ and a learning rate of $lr = 0.001$. The batch size for training was 64 objects, and the training process was limited to no more than 100 epochs. After training, the result from the best epoch based on the F1 metric was saved.

3D-CNN Model for Multi-Temporal Sentinel-2 Composites

a. **Cha** Since the resulting composites are composed of multiple multispectral images, each of which (see Table 1) can be treated as a single hyperspectral image, the structure of the 3D convolutional neural network was used as the basis. It is important to note that the model should be trained separately on each composite, as tree species may vary from season to season and the input data of different years do not fit each other.

Compared to the baseline model, adjustments were made to the stride, output linear layer sizes, and the number of channels in the input data. Below we present a detailed structure of the modified network. Input data is a collection of patches of size 1xNx9x9, where N is number of spectral channels. The presented network corresponds to N=310 (the composite of 2023).

Conv 1 Kernel (10x3x3)

Stride 3x1x1

Output 32x101x7x7

Conv 2 Kernel (5x3x3)

Stride 3x1x1

Output 64x33x5x5

Conv 3 Kernel (3x3x3)

Stride 1x1x1

Output 64x31x3x3

Conv 4 Kernel (3x3x3)

Stride 1x1x1

Output 64x29x1x1

Linear 1 Input: 1x3712

Output: 1x128

Linear 2 Input: 1x128

Output: 1x13

Through experimentation, it was determined that the best classification results, according to the accuracy metric, were achieved with the following training parameters: weight decay $wd = 0.006$, learning rate $lr = 1e - 05$, batch size $batch\_size = 64$, $eps = 1e - 06$.

b. Data Preparation

The territory of the Krasnosamarsky forestry is characterized by a highly uneven distribution of areas corresponding to different forest species. As seen in Table 2, the number of pixels dominated by pines is 1,611 times greater than the number of pixels dominated by elm and 67 times greater than the number dominated by poplar. When training a classification model on such imbalanced data, there is a risk of shifting the focus toward the most common species while achieving low recognition accuracy for rarer species. Therefore, during the research, we tested two methods for preparing the training dataset.

The first method involved retaining the original species proportions in the training dataset with training conducted on 40% of the pixels from each class.

The second method aimed to create a more balanced dataset. For that, several conditions have been introduced to improve the balance between classes when forming the training dataset:

- ✓ The number of elements in any class should not exceed 10,000 objects;
- ✓ The number of elements in a single class should not exceed 70% of the total instances of that class in the composite;
- ✓ Augmentation methods were applied to classes with a small number of elements (precisely, rotations of 90 degrees and mirroring).

The resulting number of instances for each class used to train the models is shown in Table 2.

Table 2: The composition of the Sample After Augmentation.

Tree Name	**Original Sample**	**Training Samples (Method 1)**	**Training Samples (Method 2)**
Birch	56981	22 793	10000
Elm	172	69	480
Oak	143500	57 400	10000
Willow	4261	1 705	10000
Maple	9751	3 901	10000
Aspen	114361	45 745	10000
Pine	277212	110 885	10000
Poplar	4132	1 653	10000
Ash	3237	1 295	9060
Water Bodies	27972	11 189	10000
Burnt and cleared areas	190154	76 062	10000
Buildings	1742	697	4876
Total	*833475*	*333394*	*104416*

Model Performance Analysis

a. Classification Accuracy for different years

It is necessary to analyze in detail the quality of classifier training under various conditions to evaluate their effectiveness. For now, we will set aside the potential inaccuracies of the ground truth mask. The selection of strategies for detecting changed forest areas will take place after the training process is completed.

To begin, a comparison of classification quality for different composites (2020-2023) was conducted. This analysis may help identify the dynamics of changes in classification quality over time and determine the most suitable season for training the model.

For model training, the resulting dataset was randomly split into training and validation sets in an 85% to 15%. Testing was conducted on the entire set of labeled data, including data from the training set. This approach is essential to obtain a complete class distribution mask, which allowing for the assessment of spatial relationships between different areas. Including approximately 10% of the original training data in the test sample does not significantly affect the overall accuracy of the classifier's performance. The results for composites from different years are presented in Table 3. In this table, Accuracy is used as the metric for classification quality. The data are provided for two methods of forming the training dataset.

Table 3: Model Performance by Year.

Year	**Number of Channels**	**Accuracy (3D-CNN)**
2023	310	88.68
2022	200	86.5
2021	430	87.57
2020	450	87.65

As we can see, there is no clear trend of deteriorating classification quality over time, indicating a growing deviation of the actual situation from the forest inventory data of 2013-2014. Apparently, the changes over the three years examined were not significant in scale. It can also be noted that the differences in classification accuracy are small and do not align closely with the dimensionality of the feature space.

b. Combining Different Seasons in one model

Since of each classifier’s result is a probability vector for all classes, it was hypothesized that the results could be improved by combining the probability vectors obtained for each composite. The final probability vector can then be generated by combining the existing vectors, taking into account the selected weight coefficients:

$$P = \sum_{i=2020}^{2023} p_i \, \alpha_i,$$

where p_i is probabilty of belonging to a class, α_i is the significance coefficient of the composite ($\sum_{2020}^{2023} \alpha_i = 1$), and i is a year. After grid optimization with step $\Delta = 0.1$, we found that the overall accuracy does not change significantly when varying α_i. The highest level achieved during optimization is 89.67. So the combination of 4 models adds 1% to the classification accuracy, which means that the increase is quite insignificant.

b. Detailed Evaluation of Classification Accuracy and Comparison with the SVM-based Classification Model

A detailed analysis was conducted on the results obtained by combining the outputs of several composites. Table 4 presents the confusion matrix of the classification results, while Figure 2 shows the ROC-AUC curves, clearly illustrating the relationship between the proportion of correctly and incorrectly classified pixels.

Table 4: Confusion Matrix for Territory Classification (3D-CNN).

		Ground Truth Data												
		Birch	**Elm**	**Oak**	**Willow**	**Maple**	**Aspen**	**Pine**	**Poplar**	**Ash**	**Water Surface**	**Open Spaces**	**Buildings and Roads**	**Precision**
Classifier Results	**Birch**	53138	24	86	0	0	1887	10364	0	0	181	5542	2	0.746
	Elm	0	10	0	0	0	0	0	0	0	0	0	0	1.0
	Oak	40	3	138273	0	2	2576	2287	1	0	103	2332	5	0.95
	Willow	0	35	16	4248	0	83	147	3	0	25	707	0	0.807
	Maple	52	5	582	2	9279	421	1648	1	0	23	627	0	0.743
	Aspen	414	10	1781	0	0	98839	7961	0	0	40	7581	0	0.848
	Pine	1840	38	1267	4	9	3647	243418	0	0	35	7633	0	0.943
	Poplar	0	1	124	1	0	22	148	4122	0	10	261	0	0.879
	Ash	151		17	0	0	0	202	0	3234	0	56	0	0.884
	Water Surface	108	6	999	4	0	287	112	5	0	27405	1927	0	0.888
	Open Spaces	1230	40	346	2	3	6596	10913	0	3	149	163415	1	0.894
	Buildings and Road	8	0	9	0	0	3	12	0	0	1	73	1734	0.942
	Recall	0.933	0.058	0.964	0.997	0.998	0.864	0.878	0.998	0.999	0.979	0.859	0.995	0.897

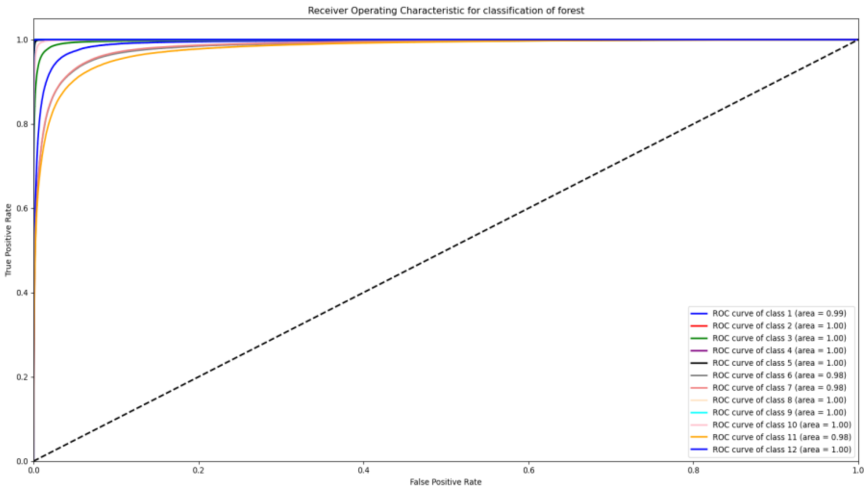

Figure 2: ROC-AUC curves for each class.

For comparison, a classifier based on SVM was trained under similar conditions, as previously described in work [2] for the same task of updating forest inventory data. This classification technology is detailed in works [2, 6, 7] and includes a procedure for spatial post-processing of classification results. As a result, a classification accuracy of 89.25% was achieved, which is very close to the results obtained by the model based on 3D-CNN.

Table 5 presents the confusion matrix for the SVM-based model. This matrix indicates that, despite the similar classification accuracy, the errors in individual classes between the two models differ significantly. This discrepancy may provide an opportunity to use both models in conjunction, as will be demonstrated later.

Table 5: Confusion Matrix for Territory Classification (SVM)

		Truth Data												
		Birch	**Elm**	**Oak**	**Willow**	**Maple**	**Aspen**	**Pine**	**Poplar**	**Ash**	**Water Surface**	**Burnt and Open Spaces**	**Buildings and Roads**	**Precision**
Classifier results	**Birch**	48520	0	73	0	5	1477	4203	0	95	166	2442	0	0,852
	Elm	0	107	0	0	5	0	38	0	0	0	22	0	0,622
	Oak	174	0	136508	3	381	2835	1390	97	6	835	1265	6	0,951
	Willow	1	0	12	3322	80	74	62	91	0	195	424	0	0,780
	Maple	64	0	360	18	7773	276	712	2	5	222	319	0	0,797
	Aspen	1503	0	2410	90	173	98222	4471	9	0	266	7217	0	0,859
	Pine	7350	0	2057	37	619	9004	245758	70	119	167	12013	18	0,887
	Poplar	4	0	110	49	23	46	29	3559	0	99	213	0	0,861
	Ash	72	0	5	0	1	10	62	0	2989	13	85	0	0,923
	Water Surface	339	0	486	52	84	295	132	96	0	24228	2259	1	0,866
	Burnt and Open Spaces	4211	0	1909	259	283	9959	9802	92	10	1611	161999	19	0,852
	Buildings and Road	10	0	38	0	0	39	28	0	0	17	506	1104	0,634
	Recall	0,779	1,000	0,948	0,867	0,825	0,804	0,922	0,886	0,927	0,871	0,858	0,962	0,892

Figure 3 displays the maps of classification results obtained using two different models. It is evident that there are significant visual differences between the two masks.

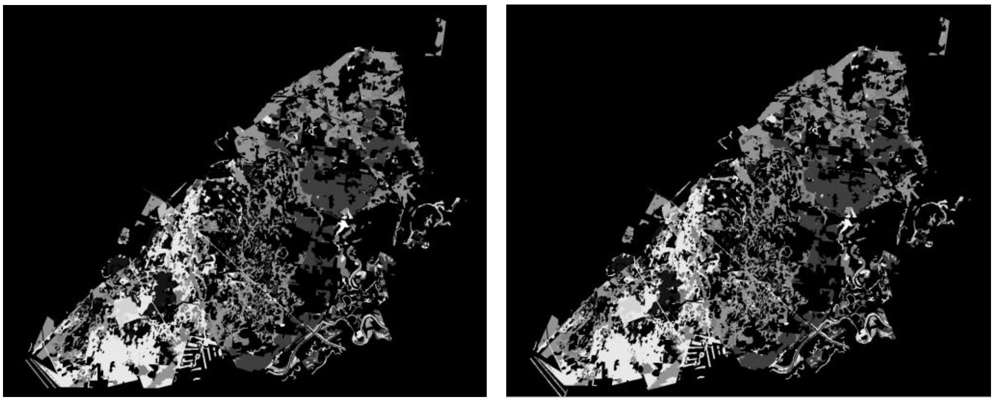

Figure 2: Classification results of the forestry area using 3D-CNN (top) and SVM (bottom).

It should also be noted that up to this point, we have considered models trained on a balanced training dataset formed using Method 2. Additionally, models based on a dataset formed using Method 1 (with 40% of training examples from each class) were also trained. This significantly increased the training time, but the classification accuracy also improved. For the SVM-based model, accuracy reached 96.78%. However, it is important to note that this value may appear inflated due to the substantial volume of training data and the evaluation of classification accuracy, which includes training examples. There is a potential issue of overfitting.

However, as noted above, the main criterion in this work is the ability of the model and the data analysis technologies using it to detect changes in the species composition of the forest from satellite images. The quality metrics of the model are therefore purely secondary. Thus, we will now turn to discussing how to apply the obtained models to address the final task.

Application of Trained Models for Detecting Changes in Forest Data

a. Evaluation of Change Detection Quality

We will denote c_{inv}, $c_{predict}$, c_{field} as the class label value at a certain validation point according to the forest management data, according to the model's prediction, and according to ground truth verification, respectively. The classification of the target area is carried out based on the species classifier when changes are detected. Subsequently, the selection of preferred points for verification is conducted according to a certain procedure. The candidate points are those for which $c_{inv} \neq c_{predict}$. Next, let's assume that a certain point has been selected for ground verification. A change is considered to be successfully detected if $c_{inv} \neq$

c_{field} although it is not necessary for the model's prediction at this point to be correct.As a result of the experiment to select the significance coefficients α_i the following results were obtained:

We will use the following metrics to assess change detection quality:

- the proportion of Type I errors (false positive predictions):

$$p_1 = \frac{\sum_{i=1}^{N}(c_{inv}(i) \neq c_{predict}(i)) \land (c_{inv}(i) = c_{field}(i))}{\sum_{i=1}^{N}(c_{inv}(i) \neq c_{predict}(i))},$$

where i is the index of the point, N – s the total number of points.

- the proportion of Type II errors (false negative predictions):

$$p_2 = \frac{\sum_{i=1}^{N}(c_{inv}(i) = c_{predict}(i)) \land (c_{inv}(i) \neq c_{field}(i))}{\sum_{i=1}^{N}(c_{inv}(i) = c_{predict}(i))}.$$

- Accuracy calculated between $c_{predict}$ and c_{field}. This metric is secondary, but nonetheless useful.

b. Preliminary Verification on Previously Checked Points

For the initial analysis of change detection quality using the trained models, points that had already been reviewed in 2023 during the preparation of article [2] were used. These points were not selected based on the predictions obtained in this work. The criteria for selecting points also differed (in the next subsection, we will outline the criteria used in this study). Nevertheless, this set of points will provide us with a preliminary understanding of the characteristics of using the examined models. It consists of 36 points, of which the species actually changed in 21 points ($c_{inv} \neq c_{field}$).

The results of the evaluation of the two models trained on balanced data are presented in Table 6. As can be seen from the first two rows, the classification accuracy for this set of points is quite low. Both models showed similar accuracy values; however, they differ significantly in the proportions p_1 and p_2. This provides a basis to apply both models and compare the obtained predictions to form a final decision. In rows 3-4 of Table 6, the metrics for two decision-making strategies are indicated: checking for discrepancies with the original class for either model and checking only if both predictions do not match the original class. As shown in the table, the first strategy significantly reduces the proportion of misses, while the second reduces false positives. Therefore, depending on the application conditions, one of these strategies can be practically followed.

Table 6: Comparison of Different Models in the Task of Detecting Forest Changes (Point Selection and Field Surveys Conducted Earlier).

Classification Model	p_1, %	p_2, %	**Accuracy, %**
3D-CNN	47.62	26.67	61.11
SVM	14.29	66.67	63.89
Two models trained on a balanced dataset: checking for any discrepancies with the original class.	4.76	73.33	66.67
Two models trained on a balanced dataset: checking only if both predictions do not match the original class.	57.14	20.00	58.33

c. Technology for Selecting the Most Priority Points for Detecting Forest Changes

Considering all the previously obtained results, the following point selection technology for detecting changes was chosen and applied in practice based on the two models:

1) The predictions of both models are used. At the initial stage, only those points for which both predictions do not match the original class are retained for further consideration.

2) We consider the plots as a whole and evaluate the percentage of pixels in the plot p_{inv} classified into the class corresponding to the dominant species of the plot.

3) Among the remaining pixels in the plot, we identify the most common class in the prediction mask that does not correspond to the dominant species of the plot (referred to as the "secondary class") and calculate the percentage of such pixels p_{other}.

4) We discard plots where the "secondary class" is not a forest species, as we are specifically interested in changes in the species composition of the forest, rather than clearings and burns.

5) Among the remaining plots, we discard those for which $p_{other} \leq T_{other}$ and $p_{inv} - p_{other} \geq T_{diff}$, meaning we only retain plots where the "secondary class" is sufficiently prevalent.

6) The area of the connected segment within the plot, where all pixels are classified as the "secondary class," is calculated. If it does not exceed the threshold T_{area}, the plot is discarded.

7) In each of the remaining plots, we find the point that is closest to the centroid of the pixels classified by the model as the "secondary class" and is also classified into this class.

In addition, another method for detecting changes was tested separately using a single model trained on an unbalanced dataset. Due to the high accuracy rating for this case and, consequently, a lower number of errors, it was decided not to further reduce the number of candidate points by intersecting the two models. Therefore, this selection method will be practically identical to the first one, with the only difference being the absence of point 1 from the list above.

To analyze the effectiveness of the proposed technology, 20 points were selected in the field and subjected to ground verification. The points were selected with threshold values of $T_{other} = 0.2$, $T_{diff} = 0.6$, $T_{area} = 0.25\ ha$. The results of the verification are reflected in Table 7. As can be seen from the data presented, only 2 out of 20 points were selected incorrectly, resulting in a Type I error of 10%. The Type II error is zero, as we did not select points for ground verification where the classifier did not detect changes.

It is easy to see that the metrics in Table 7 are much better than those in Table 6, even though they are based on the same models. The improvement in detection quality is solely due to the technology for selecting verification points proposed in this subsection. Undoubtedly, the quality of detecting changes in forest composition at points selected using the proposed technology will decrease as the number of these points increases, since relaxing the threshold constraints (T_{other}, T_{diff}, T_{area}) will be necessary to select a larger number of points. However, the results achieved on the examined sample suggest that the proposed technology significantly reduces the labor intensity involved in the task of partial updating of forest inventory data.

Table 7: Classifiers Performance.

Points Selection	p_1, %	p_2, %	**Accuracy, %**
Two models trained on a balanced dataset: checking only if both predictions do not match the original class.	7.14	0	78.57

One model trained on an unbalanced dataset.	16.67	0	66.67
Both options combined	10	0	75

Conclusions

This study investigated the potential of efficiently and accurately updating forest inventory data using images obtained from Sentinel-2 satellites. The use of various classification models and different approaches for their application in detecting forest changes was explored. Since this task has already been addressed in previous works [2, 6], we will highlight the main results achieved in this article.

1) The classification model based on 3D-CNN did not significantly outperform the SVM-based model when evaluating the quality of forest species classification on archival forest management data.

2) The joint use of two models (based on 3D-CNN and SVM) for selecting points for ground verification improves the quality of selection compared to using a single model.

3) The use of satellite images from four seasons during model training did not lead to a significant increase in classification quality metrics; therefore, it can be concluded that a single seasonal composite is sufficient overall.

4) It is not possible to draw a definitive conclusion about which training dataset yields better results in assessing forest changes: balanced or unbalanced. For the balanced dataset, the accuracy of the model's predictions compared to archival inventory data is higher; however, both options performed well when selecting points for detecting forest changes.

5) The proposed technology for selecting priority points for ground verification has demonstrated high effectiveness and offers advantages compared to the technology previously used [2].

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