Mapping Siberian Arctic Mountain Permafrost Landscapes by Machine Learning Multi-sensors Remote Sensing: Example of Adycha River Valley

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Abstract: The landscape taxonomy has a complex structure and hierarchical classification with indicators of their recognition, which is based on a variety of heterogeneous geographic territorial and expert knowledge. This inevitably leads to difficulties in the interpretation of remote sensing data and image analysis in landscape research in the field of classification and mapping. This article examines an approach to the analysis of intra-season Landsat 8 OLI images and modeling of ASTER GDEM data for mapping of mountain permafrost landscapes of Northern Siberia at the scale of 1: 500,000 as well as its methods of classification and geographical recognition. This approach suggests implementing the recognition of terrain types and vegetation types of landscape types. The 8 types of the landscape have been identified by using the classification of the relief applying Jenness's algorithm and the assessment of the geomorphological parameters of the valley. The 6 vegetation types have been identified in mountain tundra, mountain woodlands, and valley complexes of the Adycha river valley in the Verkhoyansk mountain range. The results of mapping and the proposed method for the interpretation of remote sensing data used at regional and local levels of studying the characteristics of the permafrost distribution. The work contributes to the understanding of the landscape organization of remote mountainous permafrost areas and to the improvement of methods for mapping the permafrost landscapes for territorial development and rational environmental management.

1 INTRODUCTION

The development of knowledge-based approaches to object recognition is one of the most relevant research areas in machine learning and artificial intelligence algorithms for image processing and interpreting of the Earth observation data (Arvor et al, 2019). Landscape classification and mapping in geography are traditionally represented by the classification of the landscape types and categories according to the characteristics of the vegetation cover, soil, relief, geomorphology, lithology, etc. Permafrost landscapes are a complex geographic object in the zone of permafrost distribution and the development of cryogenic processes. They have a complex hierarchical classification structure (Fedorov, 2018). Recognition and mapping of permafrost landscapes objects are based on the multi-fusion data modeling on the territorial and geographical features of landscape components. It makes them a multidimensional object for their recognition using remote sensing data processing (Boike et al, 2015). Given the lack of geospatial data of environmental parameters, remote sensing modeling becomes one of the main available tools for understanding the spatial organization of mountain permafrost landscapes in

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the Arctic region (Witharana et al, 2021). Accurate mapping of landscapes is particularly important in view of the richness of the territory in mineral resources, as well as in assessing the possibilities of territorial development and taking effective measures for environmental management (Kalinicheva et al. 2019). In addition, permafrost landscape types are used to account for agrobiological resources, such as reindeer pastures. Landscape taxonomy has a complex structure, being a heterogeneous knowledge, so there are obvious difficulties in interpreting land use/ land cover classes for landscapes and geographical processes. The classification of permafrost landscapes used for the territory of Siberia and Central Asia is based on Milkov's theory of landscape taxonomy and fractional hierarchical classification of landscapes, represented on the Permafrost-Landscape map of the Republic of Sakha (Yakutia) in scale 1: 1 500,000 (Fedorov et al, 1989). Classification and Geographic Information System (GIS) mapping of permafrost landscapes of the Republic of Sakha (Yakutia) implemented is based on superimposed analysis of climate-geomorphological, geological, biotic, and soil factors (Fedorov, 2018). This methodology allows using the cryoindication approach to apply remote sensing data and techniques in the interpretation of vegetation cover. In addition, remote sensing data are used as a tool for drawing boundaries in the designation of permafrost parameters (such as the type of distribution, depth of occurrence, cryogenic processes), extracted from the database of the geocryological observatory, and the collection of field data. Data from multispectral images are widely used in the analysis and modeling of vegetation cover and their succession stages, as well as the thermal regime of permafrost (Shestakova, 2011) from thermal images (Kalinicheva et al. 2019). These examples allow us to see that remote sensing data is a relevant and rapidly developing tool in the study of the permafrost landscape. Machine learning and artificial intelligence algorithms (including deep learning), such as Support Vector Machine, (Pal, and Mather, 2005) and Random Forest (Eisavi, 2015), have shown significant performance in analyzing large data sets when modeling mountain permafrost landscapes on the example of Orulgan ridge in Verkhoyansk Mountains system (Gadal et al, 2020). The ability to perform complex hierarchical classifications has become the main tool for analyzing changes in the environment. At the same time, the capabilities of remote sensing data in the paradigm of geographic processes and complex geosystems (landscapes), including a set of heterogeneous knowledge, represent a significant gap in the representation of geographic knowledge in image analysis. Research on the development of a methodology for mapping and recognizing permafrost landscapes is increasingly combining machine learning and artificial intelligence methods in the analysis and the interpretation of remote sensing data with geographic knowledge and geographic classification (Huang, 2020). In this study, we aim to develop a mapping methodology of permafrost landscapes at an average scale of 1: 500,000 through modeling of intra-seasonal Landsat 8 OLI images and digital elevation model (DEM), while building a knowledge-based approach to image analysis and considering two main principles. The first principle is a classification of permafrost landscape types, made according to the approach of permafrost-landscape classification and using the criteria for their recognition for the possibilities of correlation with another research. The second principle is the application of multi fusion model for integrating the results of image classification into a spatial database that should be based on determining the relationship between the ontological status of image objects and objects of permafrost landscape.

2 METHODS AND MATERIALS

2.1 Study Area

The study area has a size of 60x80 km, and it is located between 66°26' - 65°53' North latitude and 136°27' - 138°13' East longitude. This is the basin of the Adycha river, which is the largest tributary of the Yana River. Mountains belong to the Chersky range (Adyche-Elginsky plateau) in North-Eastern Siberia. According to the permafrost landscape map of the Republic of Sakha (Yakutia) (Fedorov, 2018), this Arctic region consists of mountain deserts, mountain tundras, and mountain woodlands, as well as intrazonal valley landscapes of mountain taiga and mountain tundra. Medium-high mountains of the study area are characterized by significant dissection. The height above the sea level of the watersheds ranges from 289 to 1715 m. Permafrost type is mainly a continuous area of frozen strata from 80-100%. The thickness of the permafrost ranges from 200-400 meters. In addition, according to the permafrost landscape map, 7 types of landscape vegetation and 10 types of mountain-slope and valley areas are distinguished in the study area (Figure 1).

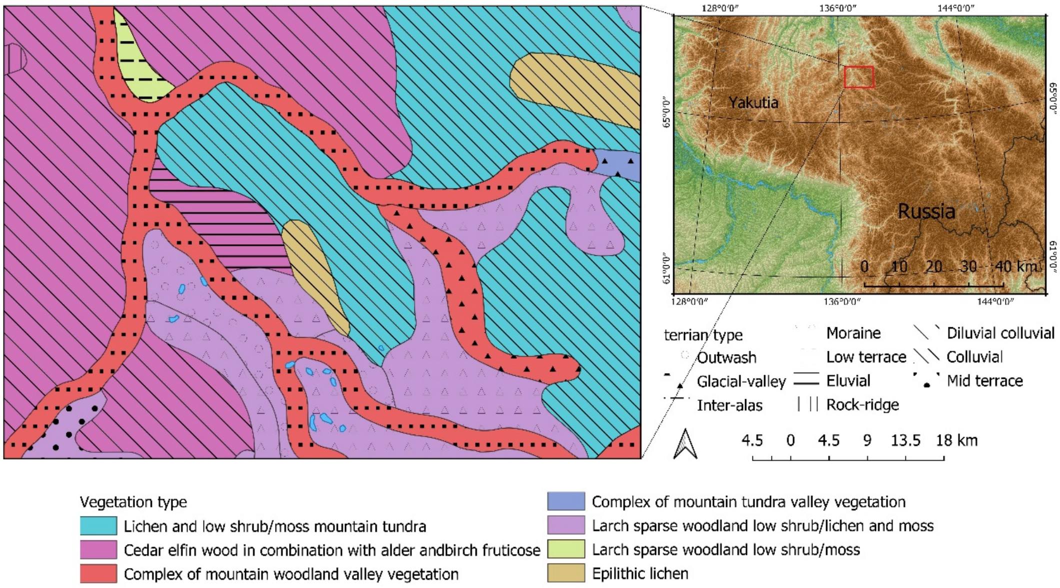

Figure 1: The study area and fragment from the Permafrost Landscape Map of the Republic of Sakha (Yakutia) on Scale 1:1 500 000 (7 vegetation types and 10 terrain types).

2.2 Data and Methods

In this study, we used hybrid data fusion modeling for landscape recognition based on the classification of multispectral images based on differences in photosynthetic activity of different vegetation types during the growing season, classification of landforms using TPI (Topographical Position Index) and methods for mapping the permafrost landscape. This allowed us to synthesize methods for classifying objects (classes) of the Earth's surface, which are closely related to the characteristics of data (mainly spectral, spatial, radiometric, and temporal resolution) with categories of permafrost landscapes. The Landsat 8 OLI images and DEM data with a spatial resolution of 30 m we used. This kind of remote sensing is suitable for landscape mapping on a scale of 1: 500,000 to 1: 100,000. These local scales are intended to reveal in maps the spatial organization of the landscape in scales of the types of landscapes, and the types of terrain. At the same time, we follow the criteria for selecting terrain types and landscape types used in the permafrost-landscape mapping.

Terrain types are recognized by the correlation of stratigraphic-genetic structure and geomorphological structure of territory. In landscape types, the recognition criteria are classes of vegetation associations (vegetation unit). In previous studies (Gadal et al, 2020) we have based analysis on the reclassification of a series of multi-time land covers for vegetation association recognition. In this study, we conduct a combined classification for three vegetation indices. This method has increased the level of automation for selecting vegetation types in permafrost landscapes (Figure 2). Landsat 8 OLI images acquired on 15 June 2018, 31 July 2018, and August 27, 2018, were used in this study. A preprocessing procedure was performed with multispectral channels (radiometric calibration, atmospheric correction using the DOS method (Dark Object Subtraction)).

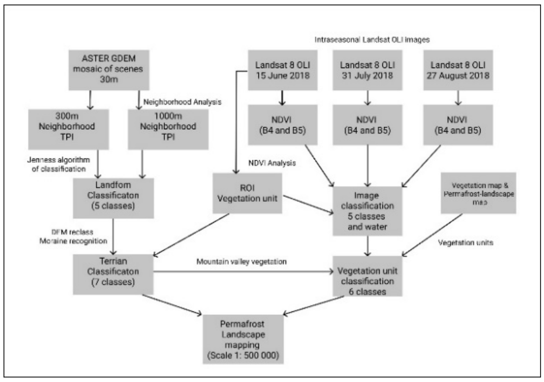

Figure 2: Modeling workflow of the permafrost landscape approach.

Relief data are collected by merging the ASTER GDEM scenes into a mosaic. The ASTER GDEM (Global Digital Elevation Model) product developed by METI (Ministry of Economy, Trade, and Industry of Japan) and NASA is based on data from the ASTER sensor of the Terra satellite. ASTER GDEM is the most improved DEM dataset that has been GDEM3, released in 2019 available at 30 meters' resolution (Abrams et al 2020). It covers an area up to 83 latitudes and has high detail for mountainous areas.

3 RESULTS

3.1 Terrain Types by Landform Classification using Topographic Position Index

The main factor in determining the types of terrain is the topography, geomorphological and lithological features of the rocks. This means that the stratigraphic-genetic complex, namely the nature of surface deposits determines the type of terrain. There are 10 types of the accumulative valley and mountain-slope areas on the territory of the study (Fedorov, 2018). The boundaries of the slope types of terrain are determined by its "upper" contact with the flat surface of the watershed, and on the other side - by the "lower" junction with the floodplain or above-flood-terrace types of terrain. The transition of slopes to accumulative valley areas is carried out using a well-defined bend along the rear edge of the valley floor. An exception to the recognition principle is the type of inter-alas terrain, which is distinguished in flat-plain territories with the development of thermokarst formations (Savvinov, 2002).

TPI is often used for automatic calculation of geomorphometric properties of the earth's surface (Weiss, 2001, Jenness, 2006, Ratajczak et al, 2009). Terrain types are determined according to their comparison with landforms determined by comparing TPI values. GRASS GIS (neighborhood analysis) and QGIS software for TPI and slope position are implemented for the processing with ASTER GDEM.

Positive TPI (>1) values represent locations that are above the average for their surroundings, as defined by the neighborhoods. Negative TPI (<-1) values represent locations that are lower than their surroundings. TPI values close to zero (1>TPI>-1) are either flat areas or areas of constant slope (where the slope of the point is significantly greater than zero). By defining thresholds for continuous TPI values at a given scale and checking the slope for values close to zero, terrain types can be classified into discrete slope position classes (Jenness, 2006). Through neighborhood analysis, TPI's are generated in scales 300 m (Figure 3, c) and 1000 m (Figure 3, d).

Using the GIS-based Jenness landform classification algorithm (Jenness, 2006), we were able to identify 5 types of terrain: eluvial (rocky and mountain top), colluvial (steep mountain slopes), diluvial-colluvial (foothills and lower parts of slopes), river valleys and glacial valleys (the bottom of the trough valleys) (Figure 4). We had to combine inter-alas and outwash and mid-terrace.

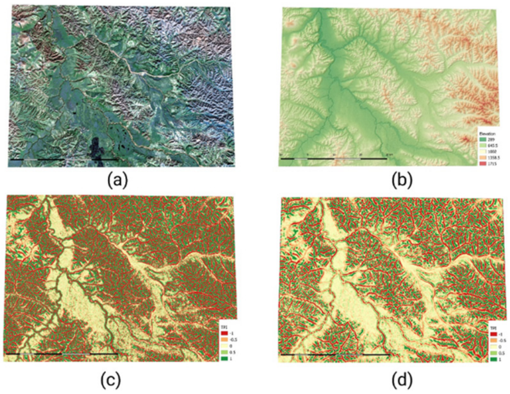

Figure 3: a) RGB (2-3-4 bands) Landsat 8, 27 august 2018; b) DEM 30m, mosaic of ASTER GDEM scenes; c) 300m Neighborhood TPI; d) 1000m Neighborhood TPI.

Determining the moraine type of terrain based on slope analysis is difficult. When solving this issue, we used the color composite of 2-3-4 bands of Landsat 8 of a summer image that can determine the side moraines designed when the glacier melts into the valley slopes in the form of ramparts or moraine terraces.

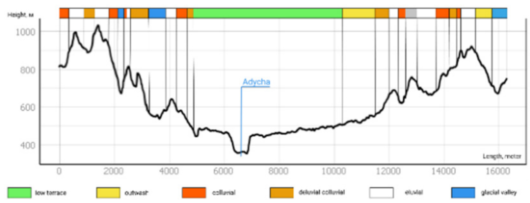

Figure 4: Hisometric profile with terrain types of Adycha river valley.

The low-terrace type of terrain is determined by the height of the valley section with a threshold of 500 m. According to the criteria for identifying low terraces, only the Adycha river valley is located below 500 meters. The valley of Adycha River of a large tributary belongs to well-drained low-terraced terrain types.

The map of terrain types (Figure 5) shows a significant difference in the spatial distribution of terrain types, in comparison with the permafrost-landscape map, while the general pattern remains. The Adycha river basin in the study area is characterized by a strongly dissected and well-drained accumulative plain and by the presence of many trough glacial valleys.

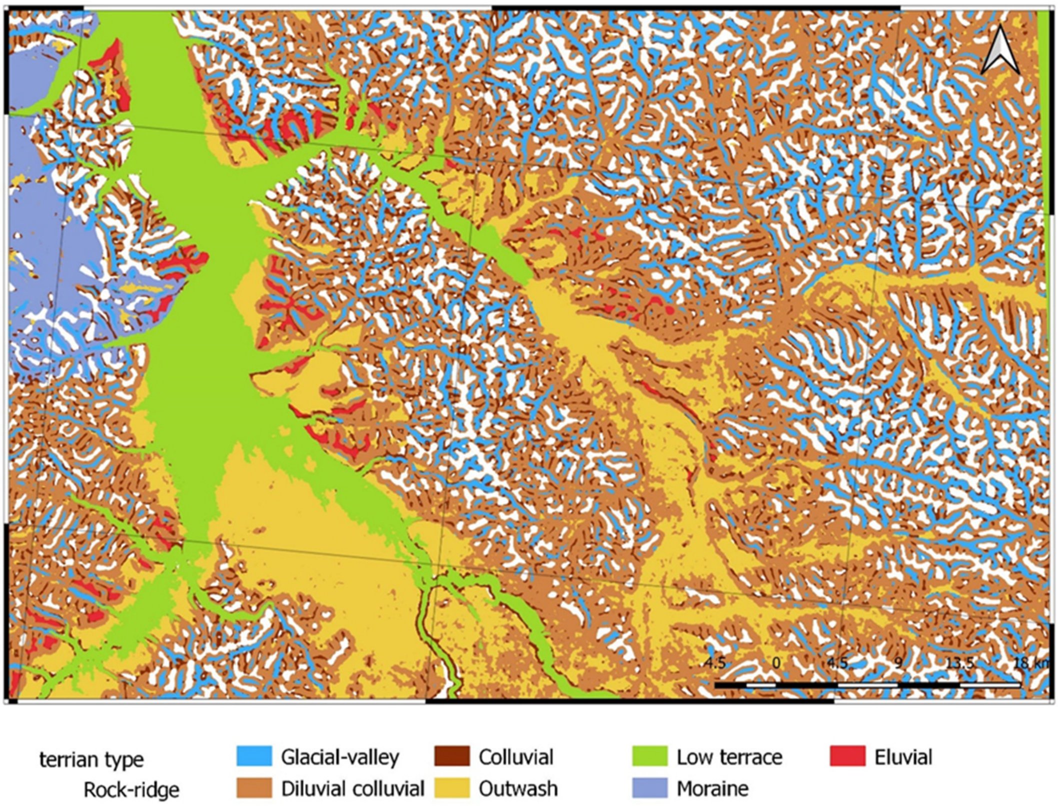

Figure 5: Permafrost landscape terrain type map by ASTER GDEM/ Scale 1:500 000.

3.2 Vegetation Unit of Permafrost Landscape Recognition

For the interpretation of the vegetation types, we applied the method of using the series of intra-season multispectral satellite images. The processes of accumulation and destruction of chlorophyll and changes in the water content in them are associated with phenological cycles and cause variations in the spectral-reflective characteristics of vegetation (Stytsenko, 2018). The seasonality of the behavior of vegetation is the result of micro and macroclimatic aspects, as well as the activities of other living organisms (Dyah et al, 2012). While for permafrost landscapes, a significant impact is made by cryogenic processes and seasonal dynamics of the thawed permafrost layer. Since the dependence of the spectral brightness coefficients on the wavelength varies not only for different objects but also for the same objects depending on the chlorophyll state and humidity, first, it depends on the vegetation phase (Stytsenko, 2018). This method based on phenological patterns is actively used to classify cropland and pastures by vegetation indices of time-series images from Sentinel-2 (Belgiu and Csillik, 2018) and MODIS. This method is particularly applicable to woodlands and valley complexes, where the sparsity of the tree layer allows satellite images to capture the spectral reflections of shrubs, bushes, and grass, underlying forest surface, playing a leading role in the typification of classes of vegetation associations. This feature and advantage allow us to increase the quality of differentiation of objects depending on the type of shrubs or herbage of larch woodlands (Elovskaya, 1989).

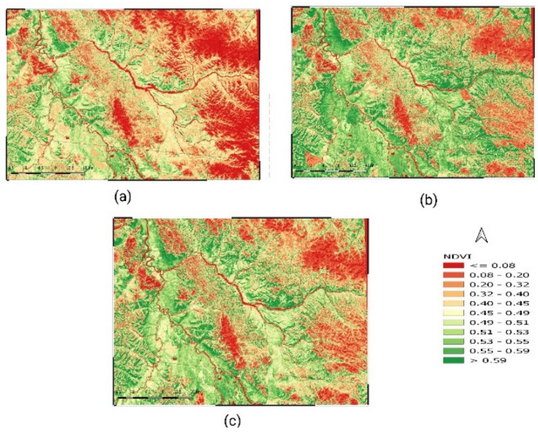

Figure 6: a) NDVI on 15 June 2018; b) NDVI on 31 July 2018; c) NDVI on 27 August 2018.

The classes of plant associations for training the algorithm for the classification of vegetation associations are based on geobotanical studies of the Chersky ridge, as well as on the types of vegetation identified on the agricultural map of the Yakut ASSR. A detailed geobotanical description of the study area is presented in the works of Nikolin E.G. (Nikolin, 2009) Kuvaev V.B. (Kuvaev, 1960), and others. Within the Chersky ridge, 5 main landscape-phytocenotic structures are distinguished, represented by 4 altitudinal belts and a complex of valley vegetation. In terms of floristic zoning, the study area belongs to the Western Verkhoyansk. Woodland and sparse forest represent the arboreal layer from Larix cajanderi. The shrubs are dominated by Pinus pumila, Betula divaricata, Betula exilis, while the layer of dwarf shrubs is dominated by Ledum palustre, Vaccinium uliginosum, and Vaccinium vitis-idaea. The moss-lichen cover is represented by sphagnum (Sphagnum warnstorfii, Sphagnum fuscum, etc.), green mosses, and lichens (Cladonia stellaris, Cladonia arbuscula, Cladonia rangiferina, Cetraria islandica, Cetraria laevigata, Cetraria cucullata, Cetraria nivalis, species genera Umbilicaria, Parmelia, Hypogimnia, etc.) In addition, steppe communities are formed on the slopes of the southern exposure. In the valley landscapes, small Ivanchay meadows are formed, adjacent to floodplain forb meadows. The vegetation of the valley complexes is dominated by dwarf birch-shrub and forest communities, including poplar-chasonian forests (Isaev et al, 2017).

The dataset compiled from the input images generated by the Normalized Difference Vegetation Index (NDVI) (Crippen, 1990) is a typical Vegetation Index for Remote Sensing Vegetation Analysis. This method is a local application of phenology-based image classification (Son et al, 2014). The proposed automated method of vegetation cover mapping, based on the analysis of short time series, allows circumventing the restrictions imposed by a single classification date.

The maximum likelihood (ML) classification algorithm based on calculating the probability distribution for the classes, let us evaluate whether a pixel belongs to the land cover class by Bayes' theorem. This algorithm requires enough pixels for each learning area to compute the covariance matrix (Congedo, 2018). This algorithm is known for its high efficiency and gives the greatest advantage to the dominant classes of the study area. In addition, among the class pairs that overlap in the spectrum, ML favors the dominant class pair. Thus, ML causes the retooling of most of the dominant classes in the study area (Shivakumara et al, 2018). Training samples for vegetation classes and water are determined by the color composite (4-5-3), (2-3-4) using the vegetation map of the Yakutian ASSR (Elovskaya, 1989) to determine the spatial distribution of vegetation communities and features of their species by the analysis of NDVI during the vegetation season.

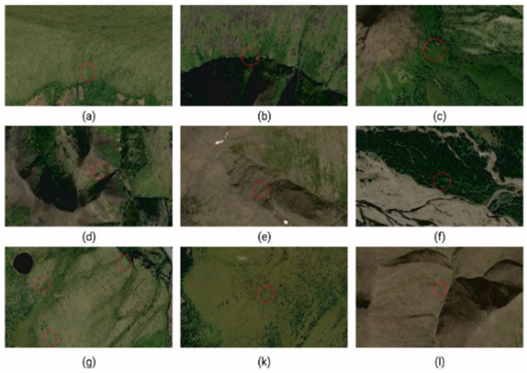

Figure 7: Yandex color composite image (CNES 2018, Distribution Airbus DS), the fragment of random point a), g), Larch woodlands lichen; b), l) Complex of mountain-tundra vegetation of trough valleys; c) Larch woodlands lingonberry green moss-lichen; k) Larch sparse green moss-sphagnum with bogs; d), e) epilithic-lichen stony deserts with areas of mountain tundra and debris of the slopes of valleys with areas of steppe vegetation; f) Larch woodlands and sparse forests with green moss shrub birches.

Data from late June shows low NDVI (Figure 6, a) responses in mountainous areas, in some areas covered with snow from heights of more than 1600 meters. High NDVI values are observed in low-terraced areas with open larch forests covered with dwarf birches and green moss. In July (peak of the green season) the spectral response of the valley vegetation complexes is almost the same with a resolution of 30 m, and the high NDVI values (Figure 6, b) are the reason for the classification for dark and light wood cover. As expected, only areas with epilithic-lichen vegetation and areas exposed to forest fires remain with zero NVDI values. In August, it is possible to separate the areas of valley larch vegetation in sphagnum bogs and in humid areas by a drop in NDVI values (Figure 6, c). In the valley areas, it is possible to clearly distinguish the areas of larch open spaces with lichens by the permanence of the average NDVI values.

When there is a real lack of ground check data at the appropriate scale, the only acceptable method for assessing accuracy is the method of generating random points and correlating the classification results with the available higher resolution data

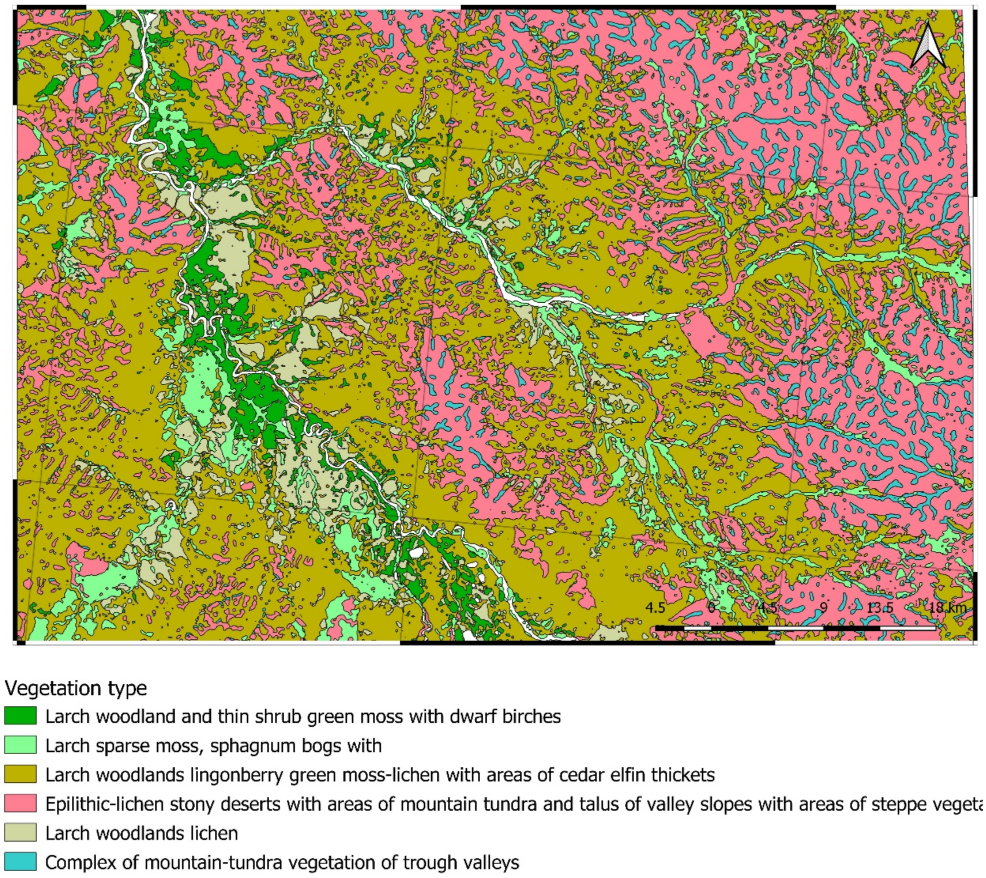

Figure 8: Permafrost landscape vegetation unit map by Landsat 8 OLI image series 2018-2020. Scale 1:500 000.

Yandex Satellite, Google Earth (Figure 7). Overall accuracy was 78% and Kappa coefficient 0,71 with 500 random points. Based on the classification obtained, a vegetation map of permafrost landscapes was created, showing 6 types of vegetation cover with an acceptable level of classification accuracy. The resulting map (Figure 8) reliably, at the present level of exploration of the territory, conveys the spatial organization of plant associations.

4 DISCUSSION

In the context of climate change and permafrost degradation, qualitative modeling is of particular importance (Fedorov, 2019). The quality of remote sensing data modeling depends on basic landscape and geographic knowledge, geobotanical descriptions of the territory, and the availability of a variety of cartographic materials in geology, geomorphology, and soil distribution. The obtained maps and the described method are intended to contribute to the development of mapping of permafrost landscapes, including by modeling remote sensing data. The results obtained can be used to create maps on a local scale that are suitable for considering the agrobiological resources of areas, but also for understanding the local cryogenic conditions of mountain territories.

By comparing maps of vegetation and terrain types, one can obtain the following information about the mountainous permafrost landscapes of the Adycha valley. The spatial distribution of classes of plant associations is uneven (Figure 8). The most widespread types are Larch woodlands lingonberry green moss-lichen with areas of cedar elfin in mountain sparse forests (47.41%), Larch sparse forests and dwarf green moss sparse forests with dwarf birch forests in mountain light forests (3%), Green moss-sphagnum larch sparse forests with marsh terraces on accumulative valleys (8.54 %), Larch woodlands lichen (6%), and a complex of mountain-tundra vegetation in trough valleys (4.5%). In total, 4 plant types make up 67% of the total land cover, 29.38% are epilithic-lichen stony deserts with areas of mountain tundra and talus of valley slopes with areas of steppe vegetation. In Adycha river valley, in low-terraced terrain types, because of the warming effect of the river, three classes of plant associations are formed, which are traced in the dynamics of the green moss index - sphagnum larch woodlands with marsh, larch woodlands, and dwarf green moss woodlands with dwarf birch forests in mountain woodlands and lichen larch forests. Epilithic-lichen is distributed on the steep slopes of the mountains of colluvial, near-watershed eluvial, and rocky terrain types.

5 CONCLUSIONS

The proposed method for recognizing permafrost landscapes formulates an approach to using algorithms for processing remote sensing data in landscape research. The criteria for combining the results of remote sensing and the geographical components of the permafrost landscape have been established. The maps obtained using remote sensing modeling are a compilation of geographical studies of a given territory used in the interpretation of processing results. Therefore, the quality of modeling directly depends on the level of conceptualization of geographical knowledge about permafrost landscapes and the study area. This approach can be implemented using spatial ontology in the future.

The method used is proposed for mapping at the local level at scales from 1:500,000, 1: 200,000 to 1: 100,000, when mapping vegetation and mesorelief of individual territories of mountain permafrost landscapes that are still difficult to access and labor-intensive for field research. The lack of opportunities to interpret cryogenic parameters (such as freezing depth, rock temperature) can be considered an obvious shortage of this study. The data obtained on the spatial distribution of vegetation and terrain types can be considered a contribution to understanding the landscape organization of mountain ranges in North-Eastern Siberia. It can also be used to study the cryogenic conditions of mountain regions.

The development of methods for mapping and classification of the permafrost landscapes and other geographic objects of the landscape is directly dependent on the level of accumulated geographic knowledge about the territory and the geographic processes. Remote sensing can be used for developing the knowledge-based approach for image processing and image analysis. This study proposes one of the possible approaches to remote sensing modeling for mountain permafrost landscapes.

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