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Remote sensing as a tool of biological conservation and grassland monitoring in mountain areas of Southeastern Kazakhstan

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Abstract

Grassland degradation, as a worldwide phenomenon, has economic and bio-conservation aspects. Degradation of mountain grasslands severely impacts the ecosystem stability in fragile mountain environments and may destroy habitats of many endemic and endangered species. One of the significant triggers of mountain grassland degradation, along with possible consequences of climate change, is massive overgrazing. Overgrazing may seriously influence the ecosystem since it results in plant composition changes, soil erosion, water regime disturbances, etc., up to the disappearance of the entire ecosystem. It is crucial to have a reliable and cost-effective instrument for the ecosystem assessment of remote and hardly accessible mountain areas supported with accurate methods of the vegetation parameters estimation since the vegetation cover is first to react to externally driven disturbances. The current study was conducted in Dzungarian Alatau Mountains, inhabited by the rare and endemic anuran amphibian *Ranodon sibiricus*, Kessler, 1886. The project of the Conservation International Foundation (CIF/326/21) was aimed at the strategy of this species conservation. The current study emphasises estimating the overgrazing risks for the amphibian population. More than two hundred ground measurements were done within the Upper Koksu Forestry and adjacent areas to provide representative data on the vegetation parameters. We tested a series of spectral indices related to vegetation biophysical parameters. We found DWSI, GrNDVI, IRECI and NDI45 indices to provide the best correlations and reasonable accuracy for remote measurements of above-ground biomass, grasscover and unpalatable grass content. Sentinel-2 data with the red-edge bands, in most cases, provided better performance. Our study confirmed the use of a single criterion (like above-ground biomass) might result in a serious underestimation of grassland degradation. Data obtained from field survey and satellite information analysis allowed the evaluation of the optimal grazing load for the Upper Koksu Forestry and provided recommendations for the Action Plan on the conservation of *Ranodon sibiricus*.

Keywords: *spectral index, above-ground biomass, overgrazing, ecosystem, monitoring*

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1. Introduction

Grassland degradation, predominately induced by grazing, is a primary factor in reducing the economic value of mountain pastures. At the same time, mountain communities are experiencing unusual climatic phenomena, such as longer and relatively warmer winters, abrupt and untimely rainfall, and unusual snowfall accumulation. The changes will not only stress the adaptive capacities of mountain inhabitants.

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Still, they will also challenge lowland communities that depend on the mountains' ecosystem services, such as freshwater, for their livelihoods. Timely and accurate monitoring of grassland changes and understanding the degree of degradation are crucial to elaborate adequate policy for the sustainable use and conservation of unique mountain ecosystems (Wang et al., 2022). A series of studies propose new approaches and algorithms to assess different characteristics of mountain grasslands. Kuang et al. (2020) developed Alpine Grassland Desertification Index for Tibetan Plateau, considering vegetation fraction, above-ground biomass and soil moisture. Wiesmair et al. (2016) used high-resolution satellite data and several vegetation indices to produce a vegetation cover map emphasising overgrazed areas in the Georgian Caucasus. Cheng et al. (2022), who used Google Earth Engine and Sentinel-2 data with a Random Forest approach to extract mountain grassland areas in China, found the accuracy of Sentinel-2 indices to be good enough for large-scale mountain monitoring. A promising approach to identifying fragmented mountain grassland was recently described by Yuan et al. (2022), who used multi-source satellite data from optical and radar sensors.

Vegetation biomass is an important ecological variable for understanding the responses to the climate system and currently observed global change, whose analysis – especially in the context of past, present and possible future climate changes – is one of the crucial environmental challenges of the twenty-first century. The impact of changes in green biomass on the greenhouse gas balance and the future evolution of climate change is critical. The economic value of grassland depends not only upon the biomass but upon the plant species composition, as degraded pasture contains a high proportion of unpalatable species, substituting natural plant communities. The high content of unpalatable grasses may provide a false image of the pasture capacity, as the remotely sensed biomass is still high; however, a significant part of that biomass is unusable.

Complex analysis of grassland biophysical parameters, like above-ground biomass (ABG), grasscover and unpalatable grass content (UPG), is required to estimate pasture condition and provide well-based recommendations on the grassland use in each case study.

The impact of changes in vegetation biomass is highly relevant to estimate current conditions and probable future scenarios of ecosystem evolution. Above-ground biomass (AGB) influences environmental processes, such as the hydrological cycle, soil erosion and degradation, especially in semi-arid areas (Eisfelder et al.,2012). Remotely sensed satellite data are well-known and effective in vegetation monitoring. Due to the high reflection of chlorophyll in the infrared spectrum, NIR reflectance spectroscopy has proved to be very effective for analysing grassland biophysical parameters like above-ground biomass (AGB), the proportion of dead material, health and moisture conditions of plants, etc. The red-edge spectral region (680–740 nm), the peak of maximum reflectance region (900 nm) and the moisture-sensitive feature around 970 nm have been widely investigated in the literature (Vescovo et al., 2012). Another advantage of red-edge bands is the enhanced distinction between grasslands and shrub encroachment in mountain ecosystems (Bayle et al., 2019).

Wetness indices, which have a strong relationship with AGB, played an important role in estimating AGB suggesting that middle infrared bands are crucial descriptors of AGB. Other traditional vegetation indexes, such as NDVI, may perform less successfully, although they are often considered "a priori" better predictors in AGB modelling. Saturation effects and the high canopy cover of meadows and pastures may explain the low performance of vegetation indices (Barrachina et al., 2015). For the current paper, we pursued two linked goals: to select the most suitable algorithms for mountain pasture capacity estimation and to apply algorithms chosen for practical usage, i.e. to provide recommendations on optimal pasture load within the area of endangered species habitats.

2. Materials and Methods

Dzungarian Alatau Mountains, where the Koksu Forestry is located, is a mountain system in Southeastern Kazakhstan. Its main ridge runs from West-South-West to East-North-East between the Ili River and Alakol Lake. The total length of the ridge is about 400 km. The entire mountain system consists of several parallel ridges. Toksanbay Ridge and Bedzhintau Ridge are connected to the main northern ridge via the bridge dividing Koksu and Borotala watersheds. High plateaus at different altitudes represent a widely spread relief pattern of the mountain system, with ancient levelling surfaces lifted in some cases up to 4 000 m.a.s.l. Glaciers, snow, and ground waters are the source of many rivers, running from the northern slope to Balkhash, Alakol and Sassykkol. Water flows of the southern slope run to the Ili River. Lower altitudes encompass desert (at the southern slope), semidesert and steppe vegetation. In the range of 1500-2400 m.a.s.l. there is a belt of forest-meadow vegetation with coniferous forests and mixed meadows. Alpine meadows with small clusters of steppe vegetation are developed in higher altitudes, where xerophytic species intrude on alpine plant communities (Gvozdetsky, Mikhailov, 1978).

Upper Koksu Forestry, the subject of the study, is located in the middle part of Dzungarian Alatau (Fig. 1) and in the upper portion of the Koksu River Basin. The Forestry area is about 1100 sq.km., and the altitude ranges from 1000-1200 m.a.s.l. to 3400 m.a.s.l.

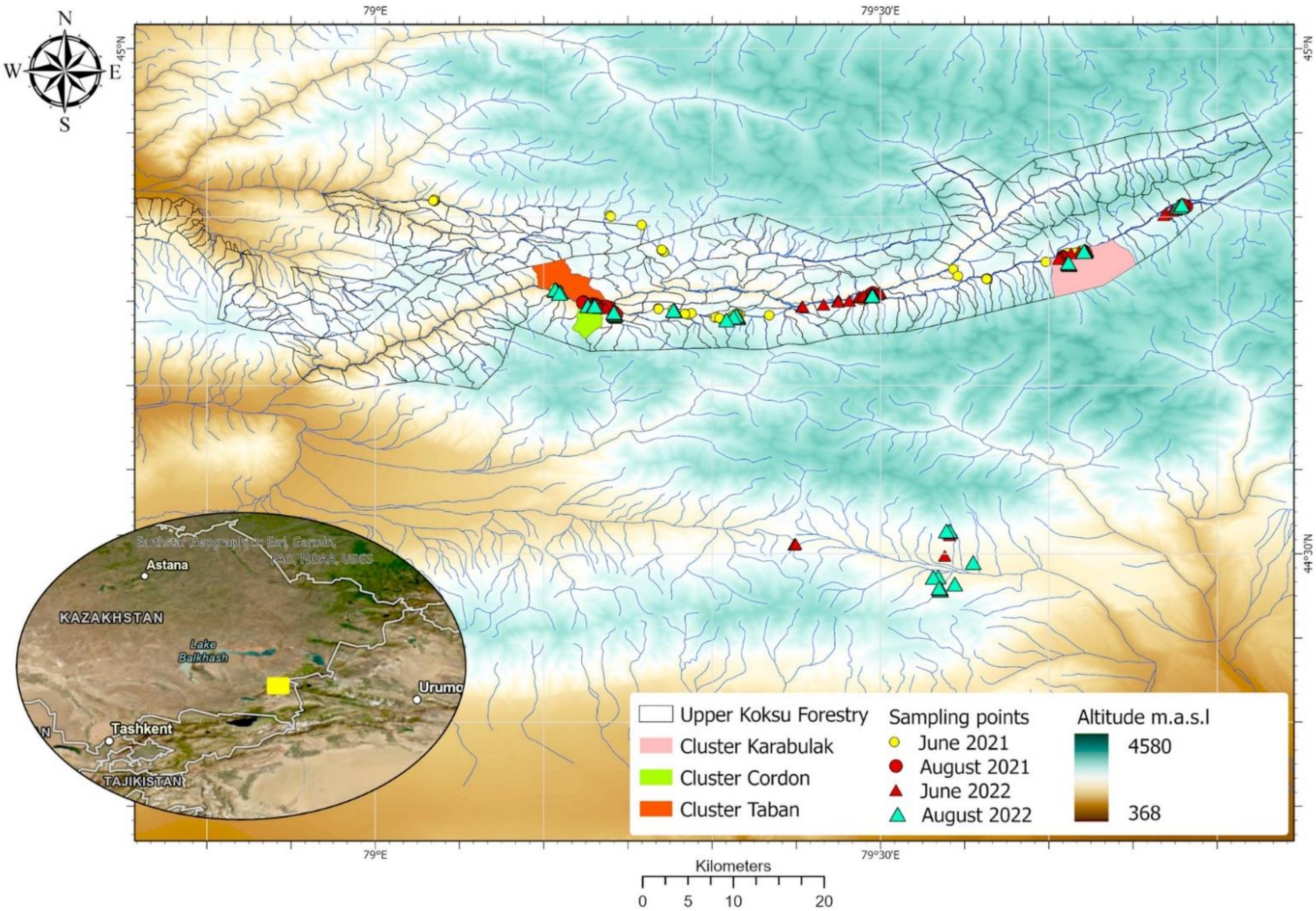

Figure 1. Study area. Upper Koksu Forestry with sampling points indicated as circles and triangles. Model sites are depicted with colored polygons.

Several field studies were attended during the summer and early autumn of 2021-2022 to gather measurements of key biophysical variables of the vegetation throughout the growing season, different grazing loads, and diverse ecological environments. Two hundred fourteen sampling points were taken to provide measurements and descriptions of plant communities. The selection of sampling plots was based upon the decision of a geobotanist and associated with the most common types of plant communities providing significant biomass. The distribution of grass communities is uneven over the study area; the intermittence of forest patches, shrubs and meadows is common in Koksu River Valley. We consider two main criteria when selecting the sampling area. First, the community should be typical for the area, i.e. the species composition should resemble the "pasture" species composition with a predominate grass community composition. Second, the area of the selected community should be large enough to be easily recognised in the satellite image. When choosing sampling areas, we also avoided the marginal topology, when the grassland is located close to the forest edge and small meadows within shrubs or trees. Three randomly selected plots (1 sq. m each) within the plant community were cut, and the grass was weighed immediately after cutting to estimate green biomass. Several points were also taken in Borokhudzir Valley – the next prominent river to the South from Koksu (Fig. 1), where no regulations of cattle amount are known. Vegetation is very poor in Borokhudzir as the area is heavily overgrazed. Biomass from a square meter does not exceed 50-60 g per square meter in this Valley. We used the minimal biomass data from Borokhudzir Valley to provide better regressions during the statistical analysis of field measurements and satellite data. Key variables measured are AGB, grasscover, and UPG.

In 2021 we also used Handheld Greenseeker to collect ground-measured NDVI as an additional variable implemented to statistical analysis to evaluate satellite and ground data consistency (Table 1).

Table 1. Field protocol (example) prepared for statistical routine.

GPS point	**Elevation, m.a.s.l.**	**Above Ground Biomass, g**	**Greenseeker NDVI**	**Grasscover, %**	**UPG, %**	**Soil Type**	**Plant Community**
001	1673,3	414	0,62	80	30-40	Chernozem	Mixed grass
002	1671,8	317	0,56	80	30-40	Chernozem	Mixed grass

The expert botanist estimated grasscover (in %) by standard geobotanical methods (Bykov, 1978). UPG (in %) was derived as a fraction of the entire grasscover by an expert. Each ground point was provided with a description of the plant community, soil type, and landscape characteristics. The landcover map used to discriminate pastures and other land categories has been developed with Forest-Based Classification of ArcGIS PRO 3.0.3 trained on ground truth points gathered during the fieldwork. Calculations of biophysical indicators of pastures (AGB, grasscover, UPG) were carried out using Landsat-8 and Sentinel-2 satellite data, synchronous with the dates of ground surveys. The following satellite images were used to analyse correlations of ground and remotely sensed data (Table 2):

Table 2. Satellite data used in the current study

Landsat 8	**Sentinel 2**
LC08_L1TP_148029_20210602_20210608_01_T1	L1C_T44TLQ_A022196_20210606T054239
LC08_L1TP_148029_20220621_20220621_02_RT	L1C_T44TLQ_A022339_20210616T054536
LC09_L1TP_148029_20220715_20220719_02_T1	L1C_T44TLQ_A028059_20220721T054221
LC08_L1TP_148029_20220824_20220824_02_RT	

We used the standard ENVI 5.3 (for Landsat data) radiometric calibration and atmospheric correction routine. Sentinel-2 imagery was processed with SNAP Desktop 9.0. Satellite imagery taken over mountain regions is expected to be radiometrically more complex than scenery taken from flat terrain. The amount of incoming and reflected radiation for the same objects might significantly differ in the mountains depending on the slope, aspect, and altitude. We studied different spectral indices to select those performing better in mountain areas as following: Atmospherically Resistant Vegetation Index (Kaufman, Tanre, 1992), Transformed Vegetation Index (Tucker, 1979), Disease Water Stress Index (Galvao et al., 2005), Enhanced Vegetation Index (Liu, Huete, 1995; Huete et al., 1999), Global Environmental Monitoring Index (Pinty, Verstraete, 1992), Green Normalized Difference Vegetation Index (Gitelson et al. 1996; Gitelson, Merzlyak, 1998), Green Vegetation

Index (Todd et al., 1998), Infrared Percentage Vegetation Index (Crippen, 1990), Inverted Red Edge Chlorophyll Index (Frampton et al., 2013), Leaf Area Index (Boegh et al., 2002), Modified Soil Adjusted Vegetation Index (Qi et al., 1994), Modified Non-Linear Index (Yang et al., 2008), Modified Simple Ratio (Chen, 1996), NDI45 (Normalised difference index based on 4th and 5th bands of Sentinel-2) (Delegido et al., 2011), Normalised Difference Vegetation Index (Rouse et al., 1974), Optimised Soild Adjusted Vegetation Index (Rondeaux et al., 1996), Perpendicular Vegetation Index (Richardson, Wiegand, 1977), Sentinel 2 Red Edge Position (Frampton et al., 2013), Soil Adjusted Vegetation Index (Huete, 1988), Transformed Difference Vegetation Index (Bannari et al., 2002), Transformed Soil Adhusted Vegetation Index (Baret, Guyot, 1991), Weighted Difference Vegetation Index (Clevers, 1989), Visible Atmospherically Resistant Index (Gitelson et al., 2002), Visible and Shortwave-infrared Drought Index (Zhang et al., 2013).

For the current project, it was not a primary goal to compare the performance of different vegetation indices. The mission of the project was to estimate the overall ecosystem condition from many views, including possible overgrazing influence on the habitat of endangered endemic amphibian species. So we omit the detailed description of the statistical routine and just state the best-performing indices. The regression analysis of the series of spectral indices calculated for Landsat and Sentinel-2 allowed the selection of those indices to describe biophysical parameters with better correlation coefficients. For the project (Conservation International Foundation /326/21), three model sites (or clusters) were selected within the area to study the biomass variability depending on grazing load and provide a detailed description of the ecosystem: Taban, Cordon, and Karabualk. Karabulak Cluster is planned to convert into a protected area for *Ranodon sibiricus* conservation, so we use this area as an example to provide further illustrations and discussion for the current paper

3. Results

3.1. Remote estimation of above-ground biomass

The best results for Landsat 8 data were obtained from DWSI (r=0.51) (Galvão et al., 2005). Disease Water Stress Index was initially proposed for hyperspectral data. If applied to multi-spectral data, it is formulated as:

$$DWSI = \frac{nir + green}{swir_1 + red} \qquad (1)$$

where *green*, *red*, *nir*, and $swir_1$ are corresponding bands of Landsat 8 imagery. DWSI is sensitive to the moisture content in green vegetation. The equation of DWSI-based biomass for Landsat 8 data is following:

$$Biomass = -485.21 + 694.19 * DWSI \qquad (2)$$

Sentinel sensor provides more infrared bands than Landsat. The three 'red edge' bands (704-783 nm) of the Sentinel-2 multi-spectral instrument provide essential information on the state of vegetation. Several specific vegetation indices were proposed to utilise red-edge bands, and we tested red-edge indices in our study along with "traditional" vegetation indices calculated for Sentinel-2 imagery. Of all studied herein indices, the "Inversed Red-Edge Chlorophyll Index" (IRECI) (Frampton et al., 2013) appeared to have a better correlation to ground data (r = 0,7). The index formula is:

$$IRECI = \frac{nir - red}{red - edge_1 / red - edge_2} \qquad (3)$$

where *red*, *nir*, $red\text{-}edge_1$, and $red\text{-}edge_2$ are corresponded bands of Sentinel-2.

The equation of IRECI-based biomass for Sentinel-2 data is following:

$$Biomass = 18.9497 + 858.73 * IRECI \qquad (4)$$

It is preferable, when possible, to use Sentinel-2 instead of Landsat data to estimate AGB. To estimate the overall accuracy of the IRECI approach, we divided the AGB range into five classes: 1st class – less than 200 g per sq.m; 2nd class – 200-500 g per sq. meter; 3rd class – 500-750 g/sq.m; 4th class – 750-1000 g/sq.m, and 5th class – more than 1000 g/sq.m. The confusion matrix returns 75.8% of the overall accuracy. Figure 2 demonstrates the distribution of AGB within the Karakbulak cluster.

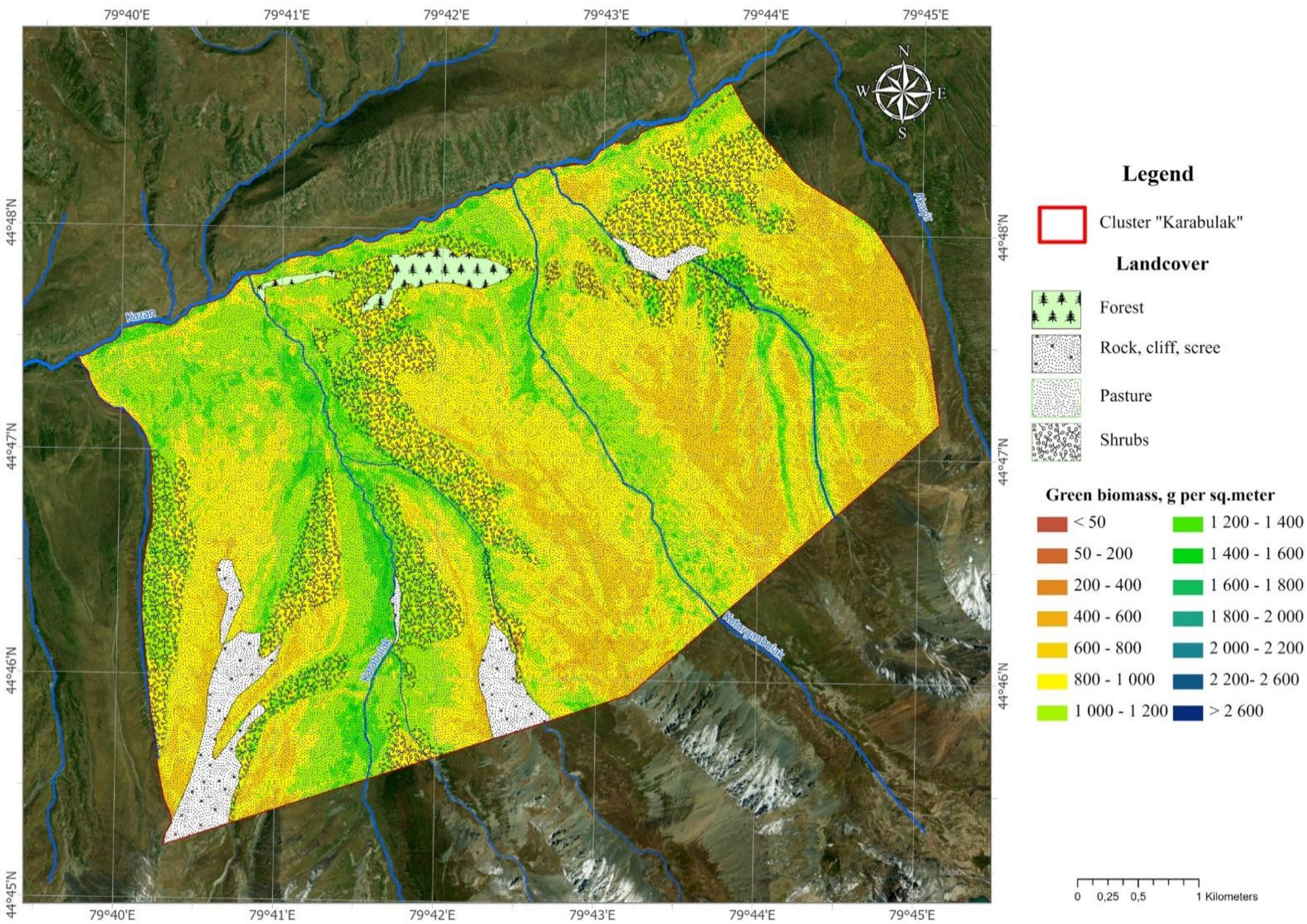

Figure 2. Green biomass estimation by satellite data (21 July 2022).

The highest AGB values referred to most plain areas along streams. The higher altitude up by the slope, the less soil wetness may be expected, and the AGB decreases following the decrease of soil wetness. This statement is valid for Grasscover as well.

3.2.Remote estimation of grasscover

Correlations of satellite VI's and ground data were studied for another essential vegetation characteristic – the Grasscover. A single index was selected for this parameter – Green Normalized Difference Vegetation Index (GrNDVI) by (Gitelson, Merzlyak, 1998). GrNDVI demonstrated a high correlation for both Sentinel and Landsat sensors (r=0.95 and r=0.93, respectively). The formula of Green NDVI is:

$$GrNDVI = \frac{nir - green}{nir + green} \tag{5}$$

where *green* and *nir* are corresponding bands of satellite imagery.

The equation to calculate Grasscover (Fig.4) from Landsat-8 data is:

$$GrassCover = 3,9398 + 127,7063 * GrNDVI \qquad (6)$$

Grasscover distribution within the Karabualk cluster is shown in Figure 3.

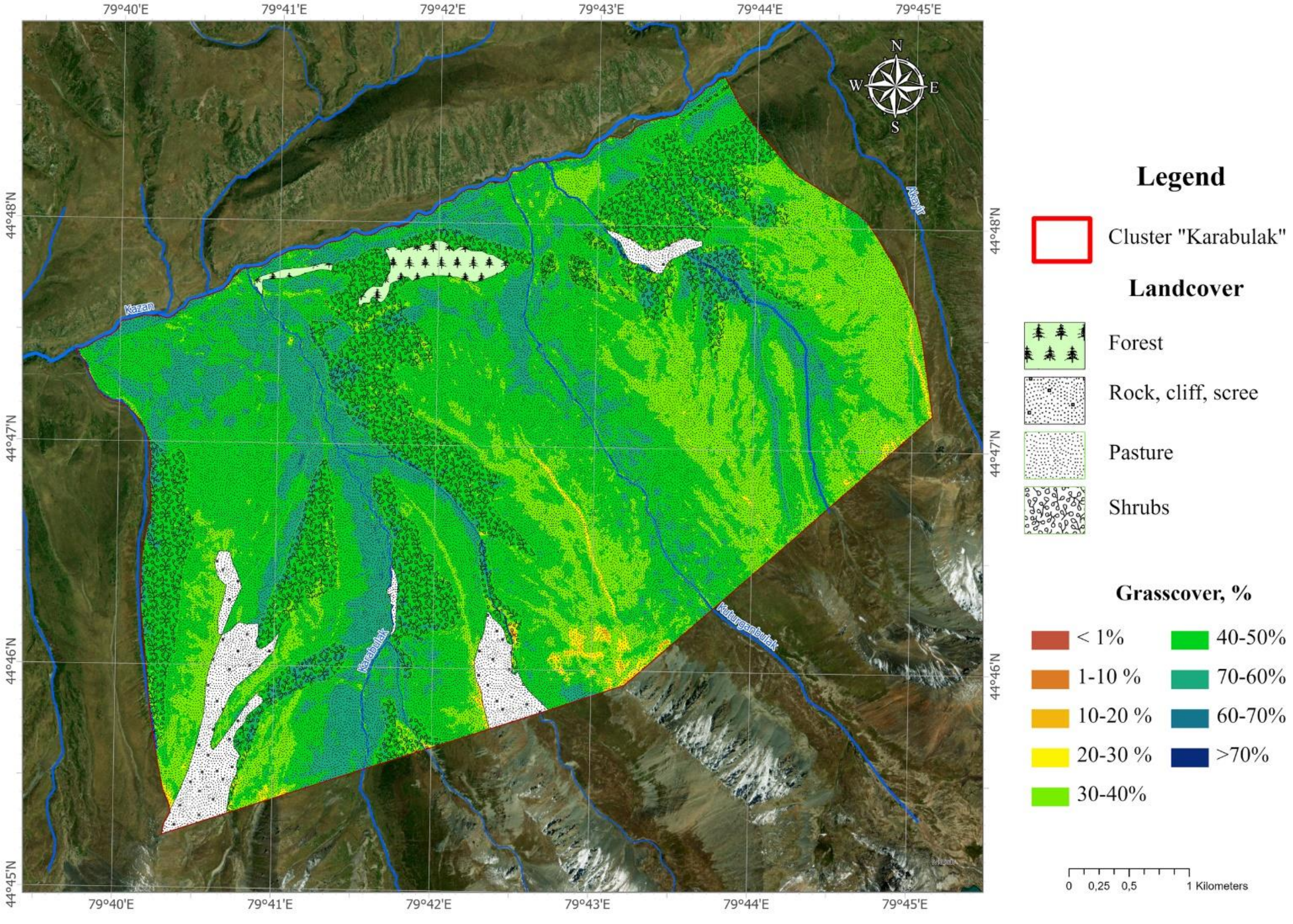

Figure 3. Grasscover estimation by satellite data (21 July 2022).

3.3. Remote estimation of Unpalatable grass content

Unpalatable and weed species content is another essential characteristic of pasture conditions. Healthy, undegraded vegetation communities may possess some weeds as marginal components with a meagre contribution to the overall biomass. In contrast, this contribution grows over degraded pastures due to replacing edible species with unpalatable ones.

The best regression (r=0,75) provided a red-edge NDI45 index developed for Sentinel-2 data (Frampton et al., 2013; Delegido et al., 2011). The formula of this index is:

$$NDI45 = \frac{rededge - red}{rededge + red} \qquad (7),$$

where *red* and *red edge* are corresponding bands of satellite imagery.

The unpalatable grass content (Fig.5) formula is as follows:

$$UPG=2.1493+132.3552*NDI45 \qquad (8).$$

UPG content within the Karabulak cluster is shown in Figure 4.

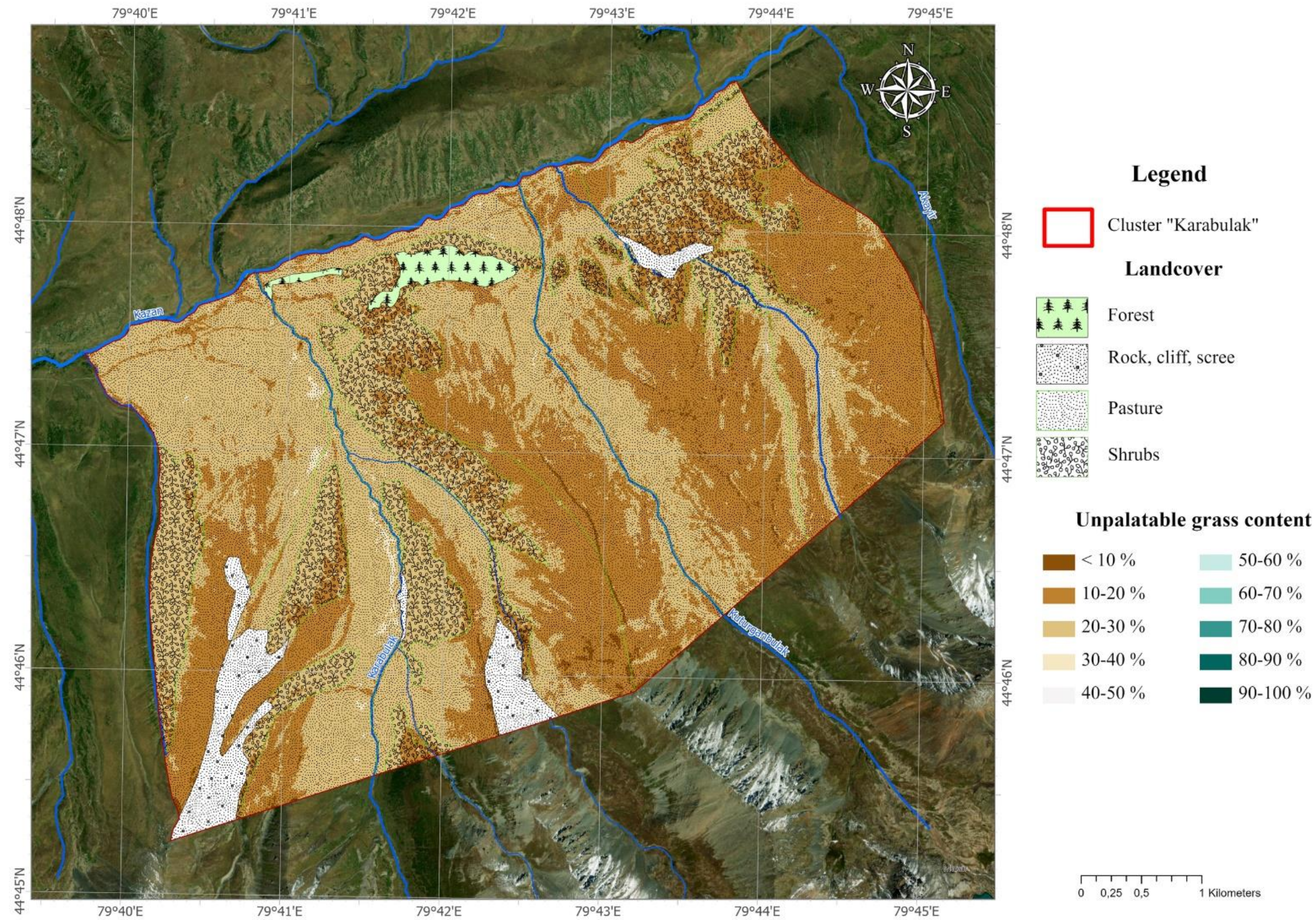

Figure 4. Unpalatable species estimation by satellite data (21 July 2022).

4. Discussion

4.1.Ecosystem degradation of mountain regions as a serious threat

The mountain systems of Central Asia represent the focus area of the regional biodiversity (Kerven et al., 2012). The unusually high endemism of local flora provides additional risks due to severe ecological damage resulting from overall degradation. The complex phenomenon of land degradation remained the region's main problem and attracted the attention of scientists from various disciplines whose studies regarded mountain regions. However, the ecosystem study is a complicated task regarding field data accessibility. The field survey stage may be time-consuming and burdensome when applied to large areas (pastoral area, district, or regional scale). Moreover, financial means or labour availability often limit the broad application of field studies. Most fundamental indicators relevant to ecosystem conditions are generally sparse for such ecosystem types that are not intensively managed. This low sampling density occurs because measuring these indicators in the field is time-intensive and expensive, especially in remote areas (Duniway et al., 2012). Yet another problem is the correct discrimination between climate- and human-induced variation in rangeland quality poses a significant challenge for developing policies to sustain herder livelihoods and alleviate herder poverty (Iegorova et al., 2019). Actual and timely information on the distant mountain pastures provided by regular satellite data may appear the invaluable source of veracious data needed to manage grasslands optimally.

The vast Koksu River Basin occupies the central position of the range of *R. sibiricus*, and this area is promising for the *in-situ* conservation of the species. As far as we know from the literature and our own experience, there are many factors limiting the well-being of the salamander populations: from natural – climate change, weather conditions, spring floods and mudflows, etc., to anthropogenic ones – first of all, cattle grazing and removal the newt from nature for scientific and commercial purposes (Narbayeva, Brushko 1986; Brushko 1993; Dolmen et al., 1993, 1999; Thiesmeier, Greven, 1997; Kuzmin et al., 1998). During our study we identified the following anthropogenically induced risk factors for the newt: 1) death of amphibians and their clutches under livestock hoofs; 2) degradation of coastal vegetation due to overgrazing provoked increase of soil heating followed by increase the evaporation from the surface and the drying up of coastal areas in general; 3) destruction of riverbanks and coastal niches (daytime and winter shelters for salamanders) by cattle; 4) a slowdown of the flow rate, stagnation of water in the channel against the background of the channel packing with coastal soil leads to the growth and development of plankton and algae, intensification of eutrophication processes and a decrease in the oxygen content in the flow; 5) the processes of eutrophication are intensified and accelerated when the channel is polluted with livestock products (manure), which is expressed, in particular, in the appearance of characteristic foam and / or traces of fat accumulations on the surface of watercourses; 6) slope erosion due to massive livestock movement.

Dzungarian Alatau, in general, is a habitat for many animals, including endangered and endemic species, like *Aquila nipalensis* (Accipitriformes), *Neophron percnopterus* (Accipitriformes), *Gypaetus barbatus* (Accipitriformes), *Ciconia nigra* (Ciconiiformes), *Ibidorhyncha struthersii* (Charadriiformes), *Ursus arctos isabellinus* (Carnivora), *Lynx lynx isabellinus* (Carnivora), *Martes foina* (Carnivora) and *Uncia uncia* (Carnivora). Among plant species inhabiting the study area, there are several endangered species as well: *Malus sieversii* (Rosales), *Aquilegia vitalii* (Ranunculáles), *Fritillaria pallidiflora* (Liliáles), *Picea schrenkiana* (Pinales), *Abies sibirica* (Pinales), *Rhaponticum carthamoides* (Asterales), *Rhodiola rosea* (Saxifragales), etc. The Dzungarian Alatau mountain system requires special attention in bio-conservation and economic aspects. As for the economy, the area, along with climate-driven desertification, is heavily affected by human activities, mainly by intense grazing. Since grasslands have the ecological functions of preventing impacts from wind, fixing sand, maintaining water and soil, conserving water, purifying the air and maintaining biodiversity, they are one of Earth's most important types of terrestrial ecosystems. As the basis for animal husbandry and the production of meat, milk and leather, grasslands have substantial economic value. Livestock consume plants according to preference and availability, affecting the composition of plant communities and the quality of grazed areas through a natural feedback mechanism: the more intensive the grazing, the more the preferred species are reduced and ultimately replaced by unpalatable ones. After a certain threshold is crossed and an unpalatable state is reached, it is difficult to reverse the change, even if grazing ceases (Inam-ur-Rahim, Maselli. 2004). Karnieli et al. (2013) documented significantly higher EVI values in overgrazed areas than in ungrazed areas. The invasion and predominant development of unpalatable species, substituting native grasses may mislead the estimation correctness as invasive species, often having denser leaf structures, induced higher spectral responses in the near-infrared (NIR) region of the electromagnetic spectrum. In repeatedly overgrazed areas, the species composition will shift from dominance by perennial grasses and forbs ('climax' species) towards dominance by unpalatable forbs and weedy annuals.

Field research during the summer of 2021 and 2022 confirms further deterioration of pasture resources within overgrazed areas. The UPG content reaches 40-50%, and the grass height does not exceed 7-10 cm (Fig. 5). In terms of satellite vegetation indices, this territory may appear to have moderately dense green vegetation, providing a severe mistake if one attempts to evaluate the condition of the pasture without correction to UPG.

Figure 5. Overgrazed, degraded area within Taban cluster. 27 July 2021 – two months after the beginning of grazing season.

An additional valuable method to obtain a reliable conclusion on pasture well-being is calculating NDVI difference during the same vegetation season. The grazing period in the Koksu River valley starts around the beginning of June when first herds appear in the lower flow of the Koksu River and start moving up to the mountains. June is a month of maximum precipitation, and it is still cold. July, a less wet but well-heated month, should provide the maximum vegetation biomass, gradually decreasing from the beginning of August to mid-September, when the first snowfalls are possible. Most herds are leaving the Koksu River Valley from mid to end of August. Following this logic, the difference in NDVI calculated for mid-July and the beginning of grazing season should indicate a significant increase of NDVI values for intact areas and, at least, minor changes for moderately grazed pastures. Figure 6 illustrates the actual NDVI dynamics from the last week of May 2022 till mid-July 2022 for Karabulak Cluster.

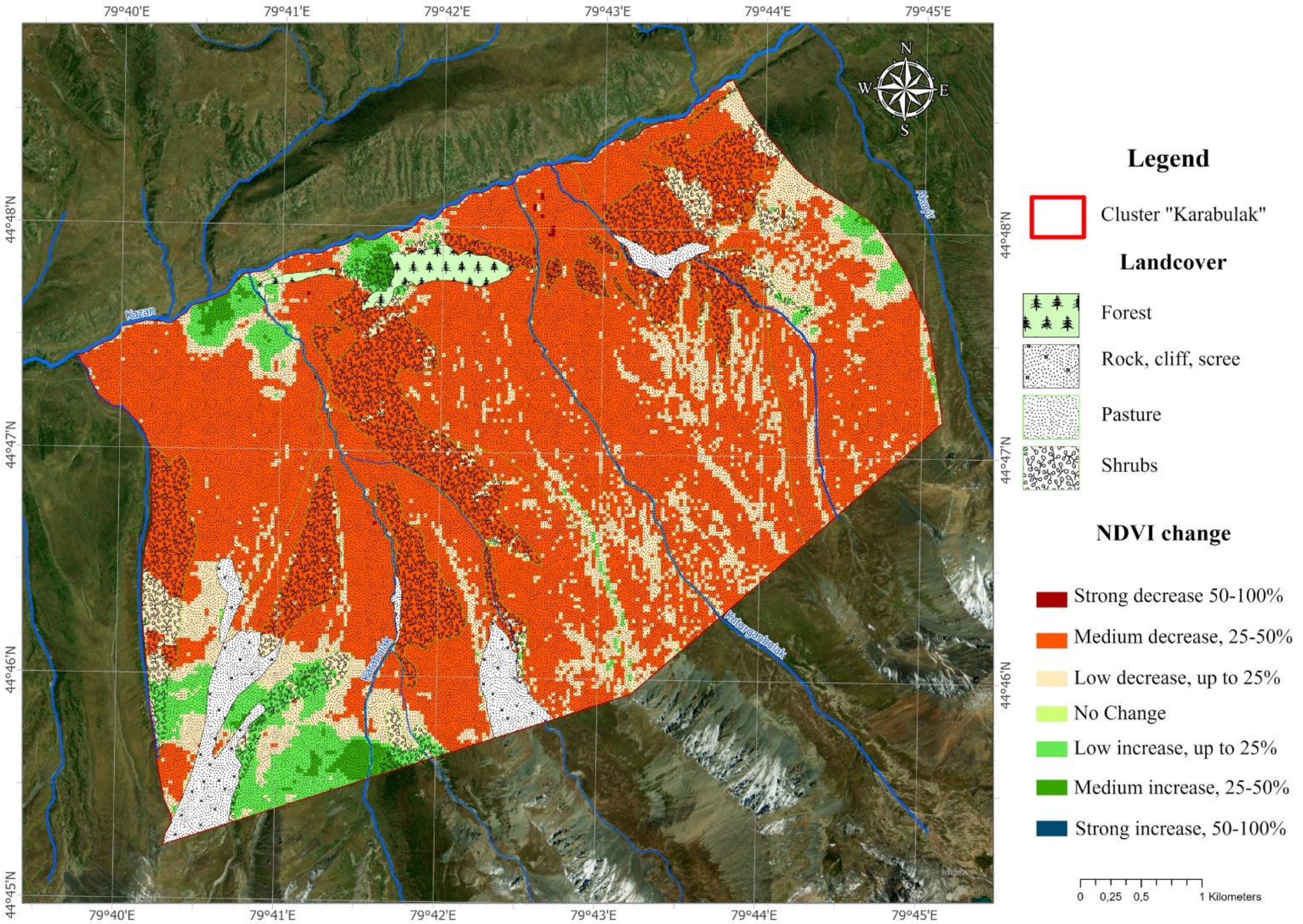

Figure 6. NDVI difference between 21 July 2022 and 20 May 2022.

The general trend of NDVI decreases from low to moderate degrees almost over the entire area of the Cluster. Such a decrease is a good illustration of possible delusion one may possess if neglecting the complex study of pasture conditions and basing it on only the vegetation index.

4.2. Using satellite data for practice: the estimation of optimal grazing load in the Karabulak Cluster

Karabulak cluster is a territory with a relatively high elevation. The altitude range varies between 2200 m.a.s.l. and 3 000 m.a.s.l. The total cluster area is about 2600 hectares. The area used for grazing (grasslands and shrublands) occupies about 2400 hectares. Intact vegetation is supposed to reach maximal AGB values in July (Rubtsov, 1948).

The average UPG content of 25-30% provides the average edible biomass at 1800 kg per hectare. We used standard approaches to estimate pasture production and define the optimal grazing loads (Alimayev 2020). Estimated feed supply (green biomass) for the area of Karabulak Cluster, calculated as

$$Feed\ supply = area*production \qquad (9)$$

is approximately 450 tons.

If we know the daily need of an animal, it is easy to calculate the optimal amount of cattle for the given area, following the equation.

$$Grazing\ Load=average\ production/(daily\ need*days\ of\ grazing\ period) \qquad (10)$$

The daily needs of livestock are well known (Alimayev 2020). It is accepted that sheep/goats require 7 kg of green grass per capita, cows – 40 kg, and horses – 50 kg of green grass. The grazing period for Koksu Forestry continues for approximately 90 days (beginning of June – end of August). With these data, it is easy to calculate the grazing load per hectare and the entire Cluster.

$$Per\ hectare\ load = (average\ production)/(daily\ need*days) \qquad (11)$$

This formula returns 2.8 sheep/goats per hectare, 0.5 cows per hectare, or 0.4 horses.

Finally, the multiplication of per hectare load to the pasture area provides an average estimation of the optimal cattle amount. It is equal to 6900-7000 sheep and goats. This estimation may vary slightly between dry and wet or warm and cold years. The cattle amount that was officially permitted to graze within the Karabulak cluster was 7200 in the year of 2020 and 7634 in the year of 2021. Unfortunately, it is impossible to calculate the actual cattle amount within the Forestry, but even official permissions gave up to 10% excess of grazing cattle. Such an excess, if continues, will lead to further pasture degradation. In the Borokhudzir River valley, where the grazing is uncontrolled, the excess of livestock leads to severe deterioration of natural ecosystems, including numerous evidence of soil erosion, mechanical destruction of shelters for endangered newts, and biochemical water pollution due to livestock excretions, making the water of springs unsuitable for autochthonous species.

5. Conclusions

Our studies in the Koksu River Valley have revealed the most suitable methods for assessing the condition and vegetable cover according to satellite data. Satellite data, especially with the red-edge bands used, appeared to be a reliable source of quantitative information for the studied area. The calculations obtained made it possible to evaluate the optimal load on the pastures, considering the real AGB corrected to the content of unpalatable grass species. Comparing our results with incomplete official data on the number of grazing cattle revealed the excess of optimal grazing load. The project in which this work has been completed is dedicated to developing measures to preserve the endemic newt *Ranodon sibiricus* in Dzungarian Alatau. The received data on the state of pastures, both in the territory of the entire forestry and for key clusters, formed the basis of recommendations for allocating the Karabulak cluster to a separate specially protected area. For the Karabulak cluster, we recommend a complete ban on the grazing of livestock, and for the territory of the forestry - a significant reduction of livestock and tightening of control measures.

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